EMPIRICAL ANALYSIS OF THE RELATIONSHIP BETWEEN ELECTRICITY DEMAND AND ECONOMIC UNCERTAINTY

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ABSTRACT

EMPIRICAL ANALYSIS OF THE RELATIONSHIP BETWEEN ELECTRICITY DEMAND AND ECONOMIC UNCERTAINTY

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The determination of the factors that influence electricity demand and the estimation of price and income elasticities are very crucial for both effective policies and consistent demand projections. The purposes of this dissertation are to investigate the determinants of electricity demand, to obtain the price and income elasticities, and to examine the effect of economic uncertainty/volatility on the electricity demand. We model electricity demand as a function of electricity price, income, urbanization ratio, weather variables, and economic volatility. This dissertation includes two panel data applications: one for the panel of provinces of Turkey covering the period from 1990 to 2001, and another one for the panel of 27 OECD countries over the period between 1985 and 2007. We employ panel data techniques. In order to check for the robustness of our results, we use different proxy measures of economic uncertainty obtained from the estimation of ARCH/GARCH models. Results show the positive significant effect of the industrial production volatility on the electricity consumption of Turkey, and the significant adverse short run impact of oil price volatility on the electricity consumption of OECD countries.

In addition, based on the results, such as the presence of feedback effects between energy and economy and limited responsiveness of electricity demand to electricity prices, as well as, considering environmental issues and supply security, accompanying to the pricing policies, the countries should give priority to the energy efficiency programs, diversification of energy resources, environmentally friendly clean electricity generation technologies, and transformation of their industries to the less-energy intensive structure.

Keywords: Electricity Demand, Panel Data Analysis, Economic Uncertainty, ARCH Models

ÖZ

ELEKTRİK TALEBİ VE EKONOMİK BELİRSİZLİK ARASINDAKİ İLİŞKİNİN AMPİRİK ANALİZİ

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Elektrik talebini etkileyen faktörlerin belirlenmesi ve fiyat ve gelir esnekliklerinin tahmini, etkin politikaların oluşturulması ve tutarlı talep tahminleri için büyük önem arzetmektedir. Bu doktora tezinin amaçları, elektrik talebinin belirleyicilerinin araştırılması ve fiyat ve gelir esnekliklerinin bulunmasına ilaveten, ekonomik belirsizliğin/oynaklığın elektrik talebi üzerine etkilerinin incelenmesidir. Elektrik talebi, elektrik fiyatının, gelirin, şehirleşme oranının, hava durumu değişkenlerinin ve iktisadi belirsizliğin bir fonksiyonu olarak modellenmiştir. Bu doktora çalışması, iki tane panel veri uygulaması içermektedir: bunlardan biri, 1990'dan 2001'e kadarki dönemi kapsayan Türkiye'nin illeri üzerinedir; diğeri ise, 1985 ve 2007 yılları arasındaki dönem içinde 27 OECD ülkesinin panel verisi uygulamasıdır. Bu çalışmada panel veri teknikleri kullanılmıştır. Sonuçların istikrarını kontrol etmek için, ekonomik belirsizliğin ölçülmesinde ARCH/GARCH modellerinden elde edilen çeşitli temsili değişkenler kullanılmıştır. Sonuçlar, sanayi üretim volatilitesinin Türkiye'nin elektrik tüketimine pozitif belirgin etkisi olduğunu ve petrol fiyatları volatilitesinin OECD ülkelerinin elektrik tüketimi üzerine belirgin kısa dönem negatif etkisinin olduğunu göstermektedir.

Bunlara ilaveten, enerji ve ekonomi arasında geri besleme etkilerinin varlığı ve elektrik talebinin elektrik fiyatlarına karşı duyarlılığının kısıtlı olması sonuçlarına dayalı olarak, ayrıca, çevresel konuları ve arz güvenliğini de dikkate alarak, fiyat politikalarıyla beraber enerji verimliliği programlarının uygulanması, enerji kaynaklarının çeşitlendirilmesi, doğa dostu temiz elektrik üretim teknolojilerinin yaygınlaştırılması ve sanayilerin az enerji yoğun yapıya dönüştürülmesi gibi konulara ülkelerin öncelik vermesinin gerekli olduğu sonucuna ulaşılmıştır.

Anahtar Kelimeler: Elektrik Talebi, Panel Veri Analizi, İktisadi Belirsizlik, ARCH Modelleri

To My Family, and especially to the Memory of My Mother,

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CHAPTER 1

INTRODUCTION

Energy consumption increases all around the world as a result of population and income growth, urbanization, and industrialization. According to the Energy Outlook 2030 report published by British Petroleum (BP) in 2013, world primary energy consumption growth is projected to be 1.6% per annum over the period from 2011 to 2030 and 93% of this growth is expected to be from non-OECD countries. Realized world primary energy consumption growth is 2.5% for the period between 2010 and 2011 (BP, 2012). Over the same period, growth rates for the OECD and non-OECD countries are -0.8% and 5.3%, respectively (BP, 2012). For the electricity consumption, nearly same figures can be observed. Energy report of International Energy Agency (IEA) in 2011 mentioned that all over the world, the demand for electricity has increased very rapidly over the last 25 years and electricity demand is expected to have the most rapidly increasing rate compared to all the end-user energy forms. According to the report of World Energy Council-Turkish National Committee (WEC-TNC) published in 2011, world electricity consumption will increase to 25 trillion kWh in 2020 and 35.2 trillion kWh in 2035 from its level of 18.8 trillion kWh in 2007, while between 2007 and 2015, electricity consumption growth of OECD countries is expected to be 1.1% compared to the 3.3% expected increase in non-OECD countries. Also, the share of electricity in the final energy consumption is expected to increase from its share of 17.3% in year 2008 to 20% and 23.5% in years 2020 and 2035, respectively.

As mentioned by Kirschen (2003), electricity is indispensable for the industrialized societies to ensure high living standards, manufacturing, economic growth, and development which can also be confirmed by the figures above. However, it is difficult to expand electricity generation capacity immediately to meet the increased consumption as most of the power plants projects need long lead times and are highly capital-intensive. As well as, the increased environmental awareness associated with the environmental problems (for example, pollution, acid rains, and climate change) as a result of the heavy utilization of fossil fuels in the electricity generation; political and economic concerns related to the high level of external dependency for energy leading to uncertainty in supply security and high burden on the current account deficit (because of high energy import costs) show that the energy policies on the demand side should be implemented, simultaneously with the supply side policies. As pointed out by Narayan and Smyth (2005) and Carlos et al. (2009), accurate estimates for income and price elasticities and understanding the electricity demand are essential to the electricity demand forecasting, investment planning, the regulation of the sector, the formulation of policies on demand management, restructuring of electricity sector, and the determination of the implemented policies' social, economic, and environmental impacts. In the literature, the estimation of electricity demand has been attracted many attention by the researchers since the pioneering study of Houthakker (1951). According to Dahl (2011), between years 1951 and 2008, more than 450 studies has been performed for the electricity demand estimation.

Electricity can be treated as a good which is demanded and supplied but, we need to distinguish it from other goods while analyzing. As electricity is non-storable, demand must be met by sufficient supply at any time. Also, electricity demand is a derived demand because, it provides services only through the use of appliances, machines, and equipments. In addition, most of the countries has experienced a transformation in the structure and organization of their electricity industries. By the progression of the restructuring process, traditional planning methods will not be appropriate, as the industry is more vulnerable to the uncertainties. Therefore, new methods and models should be developed. In this dissertation, our aims are to analyze the determinants of electricity demand, to obtain the price and income elasticities, and to examine the effect of economic uncertainty/volatility on the electricity demand. For this purpose, we model per capita aggregate electricity demand as a function of electricity price, per capita income, urbanization ratio, weather variables, and economic volatility; and restrict our attention to the aggregate level following the arguments of Pouris (1987) to obtain more stable relation and unbiased elasticities for the total economy. We expect positive effects of income, urbanization, and weather variables as higher level of economic activity, greater access to electricity, increased use and purchase of electrical appliances, and higher requirement for cooling and heating lead to increase in the electricity consumption; whereas, negative effects of electricity price and economic volatility on the electricity consumption are expected based on the producer theory and the law of demand in the consumer theory, for ordinary and normal goods, and based on the theories of investment under uncertainty and real options. In the literature, up to our knowledge, none of the studies incorporate the economic uncertainty into the electricity demand model. However, based on the theories of investment under uncertainty and real options, according to Robays (2012), uncertainty leads to delays in the production and consumption decisions, therefore affects the decisions of economic agents. As electricity demand is also an economic decision, we expect significant effect of economic uncertainty on the electricity demand.

Literature reviewed for aggregate electricity demand analysis showed that the short run and long run income (price) elasticity of electricity demand lie between 0.02 and 2.24 (-0.03 and -1.67) and 0.203 and 5.39 (-0.003 and -6.849), respectively from dynamic models, whereas studies based on static models produced the following intervals for income and price elasticities without making any distinction between the long run and the short run: (0.19 to 0.89) and (-0.09 to -0.73). Therefore, the studies produced mixed results regarding to the elastic nature of the electricity demand with respect to income and price. However, we expect the long run elasticities to be higher than the short run's as, in the short run, given the fixed stocks of electrical appliances, equipment, and machines, and other fixed factors of production, only the factors that lead to changes in the utilization rate of fixed electrical equipment stock determines the electricity demand; however, in the long run, size of stock and efficiency of electrical appliances, equipment, and machines can change as a result of change in the economic factors. In the empirical applications, we test the following hypotheses which are based on the arguments above, theory, and the previous empirical literature;

Hypothesis 1: In the long run, electricity demand is more responsive to income and price changes compared to the short run. Therefore, the pricing policies can be more effective in the long run.

Hypothesis 2: Urbanization increases the electricity demand, significantly.

Hypothesis 3: Heating and cooling requirements increase the electricity demand, significantly.

Hypothesis 4: Economic volatility leads to significant decrease in the electricity demand.

Hypothesis 5: Higher level of income leads to the higher level of electricity consumption, and vice versa (feedback hypothesis).

This dissertation includes two panel data applications: one is for the panel of provinces of Turkey covering the period from 1990 to 2001, and the other is for the panel of OECD countries over the period between 1985 and 2007. We employ panel data techniques in order to capture cross-section heterogeneity, dynamics, and trends in the electricity demand, simultaneously. "In the energy demand modeling, Griffin (1993) has identified three major developments since 1970s" (Bhattacharyya and Timilsina, 2009: 30). One of the development is the panel data methodology. "The panel data analysis approach allowed for capturing the interregional variations that can be considered to reflect the long-term adjustment process as opposed to the short-term adjustment reflected in the time series data" (Bhattacharyya and Timilsina, 2009: 30). We obtain economic volatility measures based on ARCH/GARCH models applied to the historical data. As, "autoregressive conditional heteroskedasticity (ARCH-) based measures of uncertainty have been very common, at least since their seminal application by Engle (1982) to inflation uncertainty" (Elder and Serletis, 2010: 1140). In order to check for the robustness of our results to the different proxy measures of economic uncertainty, in our study, we consider the exchange rate volatility, industrial production volatility, stock market volatility, and oil price volatility for Turkey.

Results show the positive significant effect of the industrial production volatility on the electricity consumption of Turkey in contrast to the hypothesis 4 and positive significant effect of urbanization in line with our a priori expectations and the hypothesis 2. However, the results do not verify the hypothesis 3 as the weather variables are found to be statistically insignificant. Moreover, we find supportive result for the hypothesis 4, such that, results show significant and adverse effect of oil price volatility on electricity consumption of OECD countries in the short run. Another important result of our analysis is that the electricity demand is found to be inelastic with respect to income and price both in the long run and the short run with theoretically consistent signs implying that electricity is a normal good and a necessity, but more responsive to price and income changes in the long run justifying the hypothesis 1. Panel Granger causality test indicate the bidirectional causality between electricity consumption and GDP for the panel of OECD countries confirming the hypothesis 5.

This dissertation is organized as follows. After the introduction section, we give brief information on the historical development of electricity sector of Turkey and discuss the recent developments and restructuring procedure in the Chapter 2. Chapter 3 provides literature review on the econometric studies of electricity demand. We introduce the empirical model to be employed in the Chapter 4. In Chapter 5, we present the empirical applications for the volatility modeling of important economic variables affecting the electricity demand. Chapter 6 discusses many issues on the panel data techniques. Chapters 7 and 8 are devoted for the panel data applications for Turkey and OECD. In these sections, after giving information about the data used for the empirical study, results of the various tests and estimations are presented. In Chapter 9, we summarize and interpret the results and in addition, compare with the findings of the earlier studies. In the last section of the dissertation, Chapter 10, we provide conclusions, policy recommendations, and directions for future researches.

CHAPTER 2

OVERVIEW OF TURKISH ELECTRICITY SECTOR: A BRIEF HISTORY

In this section, we give a brief information about the historical evolution of electricity sector in Turkey and discuss the recent issues. The development of electricity sector in Turkey has been analyzed by many recent studies such as, Güney (2005), Hepbaşlı (2005), Sevaioğlu (2005), Özkıvrak (2005), Atiyas (2006), Cengiz (2006), Çetin and Oğuz (2007), Erdoğdu (2007), and Sevaioğlu (2009). As the Electricity Market Law (Law No. 4628) issued in 2001 is a milestone in the history of the electricity sector in Turkey, the report published by Energy Law Research Institute in 2007 examined the structure of the sector based on the separation before and after the Law No. 4628. According to this report and Pamir (2008), the period before the law can be classified further into five periods: period of concessionary companies, municipalities period, period in which electrification supplied by public institutions, period in which interconnected system and regional thermal and hydroelectric power plants were established, period of Turkish Electricity Authority (TEK), period in which the monopoly of TEK was abolished and returned back to the concessionary companies.

In Turkey, electricity generation dates back to 1902 by a 2 kW dynamo connected to a water mill for the street lighting and residential use in Tarsus, however, the first noteworthy attempt for an electricity generation plant began by the establishment and initiation of Silahtarağa Thermal Power Plant with a generating capacity of 122 MW in 1914. Up to 1930s, the electricity service was supplied by small regional plants owned by concessionary foreign companies. According to Bahçe (2003), this situation is in line with the conclusion drawn from 1923 İzmir Economic Congress which focused on the importance of private sector participation for the economic development.

However, because of the cost (incurred with high prices) and investment problems experienced with the concessionary companies, most of the public institutions and private companies preferred to meet their own electricity needs by their own generations. In this way, they also contributed to the electrification of the provinces that they were located. However, the outbreak of the economic depression in 1929 together with the policy shift towards to the state control, this period ended up with the abolishment of contracts of concessionary firms and expropriation of their plants by the government in 1939. In the municipalities' period, electricity service was supplied first by Ministry of Public Works, and then responsibility was transferred to the municipalities. In the following period, various institutions were established in order to provide the electricity services, such as, General Directorate of Energy Affairs in 1933, General Directorate of Electrical Power Resources, Survey and Development Administration (EİEİ) in 1935, Etibank and General Directorate of Mineral Research & Exploration (MTA) in 1935 by the implementation of First Five-Year Industrial Plan, İller Bank in 1941, State Hydraulic Works (DSİ) in 1954. However, in the report of Energy Law Research Institute in 2007, this structure was critized for lacking a central authority.

In 1948, the establishment of Çatalağzı thermal plant with an installed capacity of 60 MW can be regarded as a second attempt for the development of the electricity generation sector, afterwards, in 1952, from this power plant, electricity was transmitted to İstanbul through a transmission line with capacity of 154 kV which constituted a basis for the national interconnection system. Based on the decisions taken in the First Energy Congress in 1953 for meeting the increasing electricity demand, such as, agreements on the needs for the investments on large scale hydroelectric and thermal power plants and an interconnected grid, and the establishment of a unique institution responsible for electricity services to accelerate the investments and facilitate coordination, hydroelectric power plants of Sarıyar, Demirköprü, Kemer, Hirfanlı, and Almus were installed in 1950s and TEK was established in 1970. In addition, in 1950s, two concessionary companies, Çukurova and Kepez Electric Companies, were allowed to supply electricity as a result of

Democratic Party's policy for the incentive of private sector participation; however, public sector kept its dominance in the electricity sector for long periods. In 1956, Sarıyar and Seyhan hydroelectric and Tunçbilek thermal plants were connected to the national interconnected electricity system. Ministry of Energy and Natural Resources (MNER) was established in 1963 in order to manage the policies related to energy and natural resources and its organization was arranged according to the Law No. 3154 issued in 1985. Law No. 3154 defines the establishment purpose of the MNER as follows;

> to help define targets and policies related to energy and natural resources in a way that serves and guarantees the defense of our country, security, welfare, and strengthening of our national economy; and to ensure that energy and natural resources are researched, developed, generated and consumed in a way that is compatible with said targets and policies (MNER, 2012, www.enerji.gov.tr).

Between the period from 1960 to 1980, import substitution policy was adopted as an economic policy and as this period was also characterized by the Five Year Development plans, it is called the period of planned development. In 1970, TEK was established as a monopoly such that all the electricity services provided by various public institutions, investments, planning, and operation of generation, transmission, distribution began to be carried out by one institution, TEK. All the ownership and operation of facilities owned by Etibank, DSİ, İller bank, and municipalities were transferred to TEK until 1982. During this period, large scale power plant projects were realized such as Gökçekaya, Keban, Karakaya, and Atatürk hydroelectric and Seyit Ömer and Afşin Elbistan lignite thermal power plants; and also all the provinces were connected to the national interconnected electricity system by the addition of 380 kV energy transmission line to the system. Until 1984, the electrification rate of villages was realized to be 0.73. Two oil crises in 1973 and 1979, and embargo implemented to Turkey after Turkish military intervention in Cyprus in 1974 led to huge currency loss and adversely affect private and public sector investments. This situation had also negative impacts on the electricity sector. During this period, first planned power cuts and electricity imports began in 1973 and in 1975, respectively.

Considering the economic conditions of the country in 1980, by the 24^{th} January 1980 decrees, the export-led growth policy (outward-oriented strategies) was began to be implemented and adopted. Since 1980, Turkey has adopted liberal economic policies and privatization has become the main aim of the governments. The first reflection of this economic policy in the electricity sector is the Law No. 2705 established in 1982. This law abolished the TEK's monopoly related to the construction of generation plants and therefore allowed for private sector participation into the generation sector. "Thus, Law No. 2705 can also be considered the first "Build-Operate" type of private sector participation scheme in the industry" (Güney, 2005: 24). This process has accelerated by the enactment of Law No. 3096 in 1984 as a result of the investment needs associated with high demand growth which cannot be met by state under budget constraint. This law led to the abolishment of TEK's monopolistic structure in all segments of electricity services (generation, transmission, distribution, and trade) and provided foreign and domestic private sector participation through Build-Operate-Transfer (BOT) and Transfer of Operating Rights (TOOR) contracts and autoproduction. These contracts introduced high burden on the government because of Treasury-backed purchase guarantees. "About 10 private entities were entitled to do the generation, transmission, distribution and trade of electricity within their legal district boundaries between 1988 and 1992" (Hepbaşlı, 2005: 318). In 1993, by the Cabinet Decision No. 93/ 4789 (Date: 12.8.1993) vertical unbundling of the TEK started by restructuring TEK as two separate Public Economic Enterprise, Turkish Electricity Generation and Transmission Company (TEAŞ) and Turkish Electricity Distribution Company (TEDAŞ). In 2001, Turkish Electricity Generation and Transmission Company (TEAŞ) was further functionally unbundled as three public entities: Turkish Electricity Generation Company (EÜAŞ), Turkish Electricity Transmission Company (TEİAŞ), and Turkish Electricity Trading and Contracting Company (TETAŞ). By Law No. 3996 enacted in 1994, government provided tax exemptions and Treasury guarantees in the form of "take or pay" clauses for quantities and prices to the BOT contracts for power purchase. In 1997, Law No. 4283 introduced Build-Operate-Own (BOO) contracts which is a licensing aggrement providing Treasury-backed purchase guarantees; however, different than BOT and TOOR contracts, at the end of the contract, the ownership of generation asset need not be transferred to the state but can remain with the investor. In 2000, by Law No. 4501, all BOO contracts and previously signed BOT contracts upon request become subjected to private law and international arbitration, in contrast to the previous implementation that all BOT contracts were arranged as concessionary contracts subjected to the public law. "The privatization and deregulation efforts failed to increase the private investments sufficiently in 1980s and 1990s" (Özkıvrak, 2005: 1343). Özkıvrak (2005) explained that this result is related to the uncertainty and risk caused by the frequent amendments in the laws leading to the refrainment of private investors to engage into the investment activities in the electricity sector, as well as, to the complicated bureaucratic transactions. The structure of the electricity market before 2001 is represented in Figure 2.1.

In 1999 and 2000 IMF stand-by aggrements, Turkey has committed to terminate the treasury guarantees by stages for the mitigation of the burden on government fiscal budget, in addition, to issue Electricity Market Law (EML) to restructure the sector until the end of year 2000. In order to satisfy this commitment as well as to meet the requirements of European Union legislation and standards, in 2001, Electricity Market Law (Law No. 4628) was issued and Turkish Treasury declared the arrangements for the termination of guarantees provided. Other reasons for the restructuring involve improving efficiency and satisfying investment requirements as mentioned by Özkıvrak (2005). As supportive to the Law No. 4628, many regulations was issued to clarify the implementation rules for each of the activity and term. In addition, Strategy Papers of 2004 and 2009 published by State High Planning Council "draw a time line for restructuring that includes privatization and details regarding opening Turkey's electricity market to competition" (Güney, 2005: 10) and declare the precautionary actions to maintain supply security and targets related to the resources utilized for electricity supply in the long and medium term. Another important Law related to electricity market was issued in 2005 for the utilization of renewable energy resources in the electricity generation, and in order to encourage the use of renewable resources in the electricity generation, to mitigate the Greenhouse gases, to conserve environment, and also for the enhancement of resource diversification, Law No. 5346 introduces some incentives for the investors such as purchase guarantee and exemptions from some charges and fees. In 2007, Energy efficiency Law No. 5627 was published with the aims of efficient use of energy, prevention of energy wasting, environmental conservation, and mitigation of the economic burden arising from energy costs. In the same year, Law No. 5710 was enacted in order to determine the principles and procedures for the establishment, operation, and energy sale of nuclear power plants in line with the energy plans and policies in the implementation. Lastly, because of the ineffectiveness of Electricity Market Law (Law No. 4628) issued in 2001 to ensure competition in the generation and trading segments and to generate objective nondiscriminating organization in the distribution and transmission segments, and thus to provide supply security and low cost electricity to consumers, furthermore, concerning the alignment to the European Union legislation and standard, Draft of Electricity Market Law prepared by the Ministry of Energy and Natural Resources was submitted to Grand National Assembly of Turkey by 17 December 2012. This draft introduces pre-licensing mechanism; abolishment of autoproducer licenses; removal of the EMRA's approvals on the ownership transfer of generation facilities and change in the capital share of the licensed legal entities' partnership structure, in addition, on the amendments in the main contracts of the licensed legal entities except for the license owners under tariff regulation; establishment of Energy Market Operation Company (EPİAŞ); amendments related to the distribution companies; and period extensions. The restructuring process started in the mid-1980s has gained a legal framework by Law No. 4628. The main aim of this law is explained in the first article as follows;

> The purpose of this Law is to ensure the development of a financially sound and transparent electricity market operating in a competitive environment under

provisions of private law and the delivery of sufficient, good quality, low cost and environment-friendly electricity to consumers and to ensure the autonomous regulation and supervision of this market (EML, 2001, Article 1).

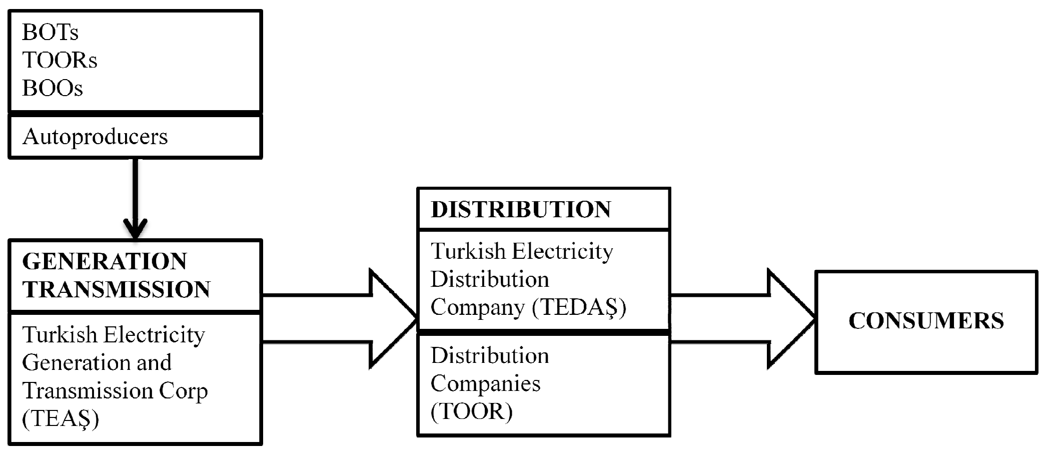


Figure 2.1 The Structure of the Electricity Market before Law No. 4628

Source: Modified from Çetin and Oğuz (2007), p. 1763.

The key features of the Law No. 4628 were summarized by Özkıvrak (2005) as unbundling the electricity sector, introducing competition in non-monopoly segments, establishing a licensing method, establishing an independent regulatory authority, identifying eligible consumers, allowing open access to distribution and transmission networks, supporting consumers with cash subsidies, establishing a national competitive electricity market, privatization. The law does not further allow for future BOT and BO contracts. By Law, in order to regulate the energy market Energy Market Regulatory Authority (EMRA) and Energy Market Regulatory Board (EMRB) were established in 2001. The duties of EMRA and EMRB are defined explicitly in the Law No. 4628, Articles 4 and 5. The structure defined in the Law

No. 4628 is shown in Figure 2.2. The electricity market basically includes generation, transmission, distribution, and trading segments. In the Law No. 4628 Article 2, the electricity market activities were defined as generation, transmission, distribution, wholesale, retail, retail sale services, trade, import and export activities and for each activity, binding procedures and principles for participated legal entities are explicitly stated in the Article 2 of the Law.

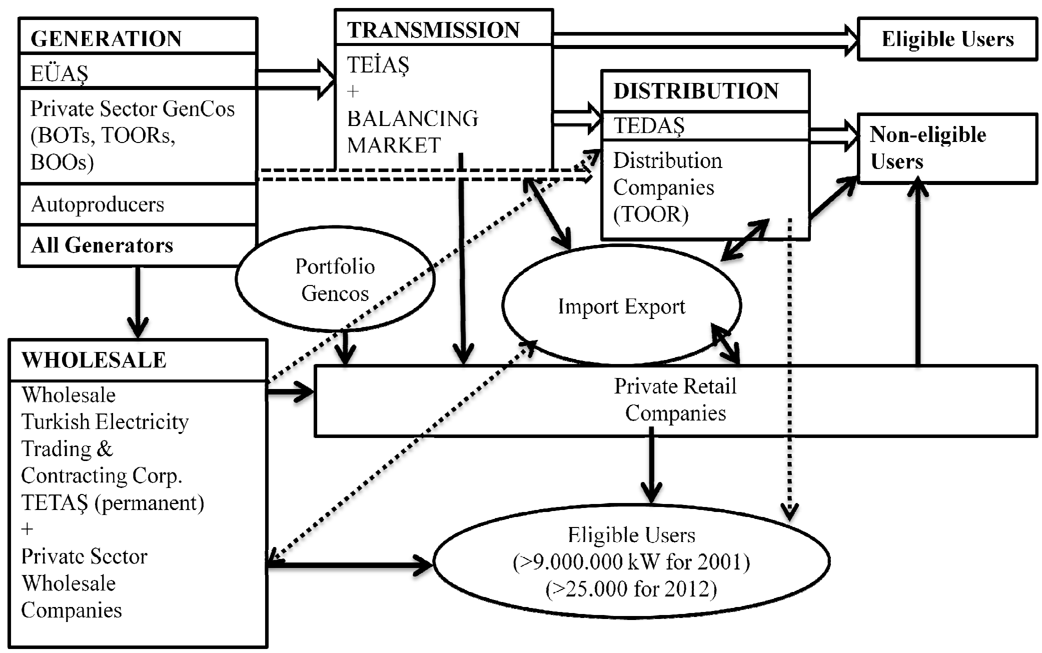


Figure 2.2 The Proposed New Structure of the Electricity Market by Law No. 4628 and 2004 Strategy Paper

Source: Çetin and Oğuz (2007), p. 1765

For each segment, based on the Law No. 4628, the participants can be classified as follows;

Generation Segment: The participants in the generation activities are Electricity Generation Co. Inc. (EÜAŞ) and its affiliates, Private Sector Generation Companies with generation licenses, Private Sector under BO, BOT, and TOOR contracts, and Autoproducer and Autoproducer Group. The electricity generation share of electric utilities is shown in Figure 2.3. The highest share belongs to the state owned company, EÜAŞ. EÜAŞ is followed by other private generators with the share of 27%. Among electric utilities, EÜAŞ was unbundled from TEAŞ and owns the generation plants transferred from DSİ besides the ones from TEAŞ. Privatization of power plants under the ownership of EÜAŞ by generating portfolio generation companies starts after the completion of distribution segment privatization according to Strategy Paper 2004. The Strategy Paper 2009 pointed out that the privatization process of the generation segment should consider supply security; climate change and environmental impacts of generation activities for the sustainable electricity market; productivity increase, reduction of losses in generation, transmission, distribution, and end-use, reduction in costs of electricity energy via competition, therefore ensuring low-cost to end-users; mitigation of external dependency by resource diversification, promotion of new technologies, and the utilization of local and renewable energy sources to the great extent; increase in the contribution of investment in the sector to the domestic value added. The privatization of generation assets are performed by Ministry of Energy and Natural Resources, the Energy Market Regulatory Authority, Ministry of Environment, Turkey Coal Enterprises and State Hydraulic Works in coordination. In this context, following the method of operation rights issuance, privatization process of 10 groups out of 18 portfolio groups with a installed capacity of 140 MW consisting of 50 river hydroelectric power plants were completed in year 2011. The pre-preparatory studies for the remaining power plants continue. Previously, in 2008, the 9 power plants under the ownership of Natural Electricity Generation and Trading Co. Inc. (ADÜAŞ) (which is affiliated to Directorate of Privatization Administration) were transferred to Zorlu Natural Electricity Generation and Trading Co. by the methods of sales and operation rights issuance. Power producers operated under BO, BOT, and TOOR contracts are subject to Law no. 3096 dated 04.12.1984, no. 3996 dated 08.06.1994, no. 4283 dated 16.07.1997 and no. 4501 dated 21.01.2000 and related regulations. The law describes the private generation companies as below and in order to prevent the exercise of market power, law limits the market share of the companies;

> private sector legal entities subject to civil law that are engaged in generation and sale of electricity at generation facility(ies) they own or have acquired through financial leasing or transfer of operating rights (TOOR). Total market share of generation facilities operated by a particular private sector generation company and its affiliates cannot exceed twenty percent of the published figure for the total installed capacity in Turkey in the preceding year. (EML, 2001, Article 2a).

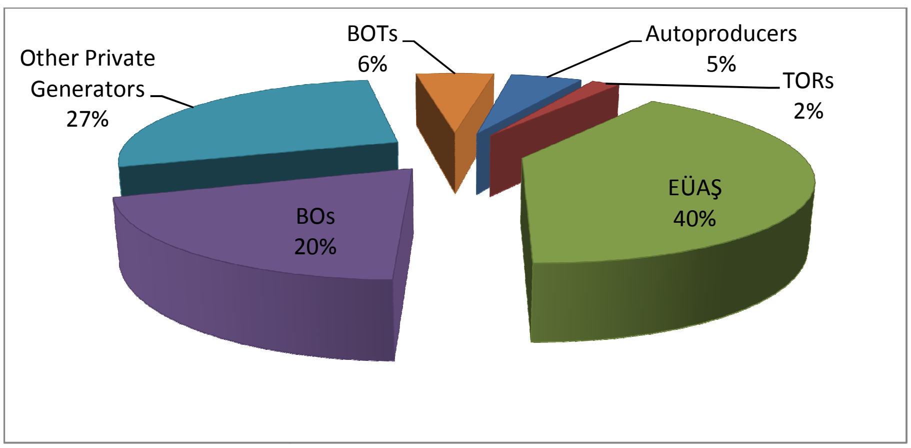


Figure 2.3 The Electricity Generation Shares of Electric Utilities for 2011

Source: EÜAŞ (2011), p. 13

Lastly, autoproducers are the legal entities that have the rights to build, operate, and own power plant for their own needs, however, law allows for the sale of at most

20% of their annual production to the electricity market. By 2001, the share of autoproducers in the total generation is 5%. However, in the Draft of Electricity Market Law, autoproducers licenses will be cancelled and removed from the type of licenses and existing autoproducers will take generation licenses without paying any license fee.

Figures 2.4 and 2.5 show the development of installed capacity and generation by energy resources between 1970 and 2011. Electricity is generated mostly by thermal power plants and wind-geothermal power plants has started generation after 1984 and regardless of incentives on generation plants based on renewable resources, by year 2011, their share in total generation and installed capacity is very low such that, 2.4% and 3.4%, respectively. If we analyze the overall development in installed capacity and generation beginning from 1923, we observe fast improvements in the installed capacity and generation. The installed capacity was 32.8 MW in 1923 and increased to 126.2, 407.8, 1272.4, 2234.9, 5118.7, 8461.6, 20337.6, 28332.4, 38843.5, 52911.1 in 1935, 1950, 1960, 1970, 1980, 1984, 1993, 2001, 2005, 2011, respectively, while electricity generation in 1923 is 44.5 GWh, increased to 212.9, 789.5, 2815.1, 8623.0, 23275.0, 30613.5, 73807.5, 122724.7, 161956.2, and 229395.1 in 1935, 1950, 1960, 1970, 1980, 1984, 2001, 2005, 2011, respectively.

Transmission Segment: TEİAŞ unbundled from TEAŞ performs the transmission system activities, such as operation, maintenance, and rehabilitation of the existing system, planning investment, "preparing, revising and inspecting the transmission, connection and use of system tariff" (EML, 2001, Article 2b). According to Electricity Market Balancing and Settlement Regulation (EMBSR) issued in 2004, TEİAŞ is also responsible for the "activities related with real-time balancing and settlement of the active electricity demand and supply" (EMBSR, 2004, Article 1) as a market operator.

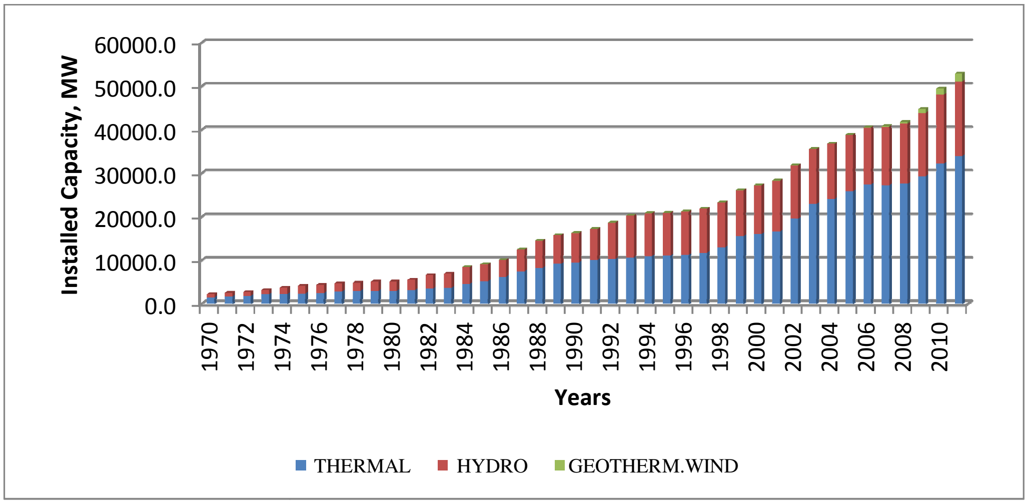


Figure 2.4 The Development of Installed Capacity between 1970-2011 by Energy Resources (MW)

Source: Produced by author using TEİAŞ (2011) data

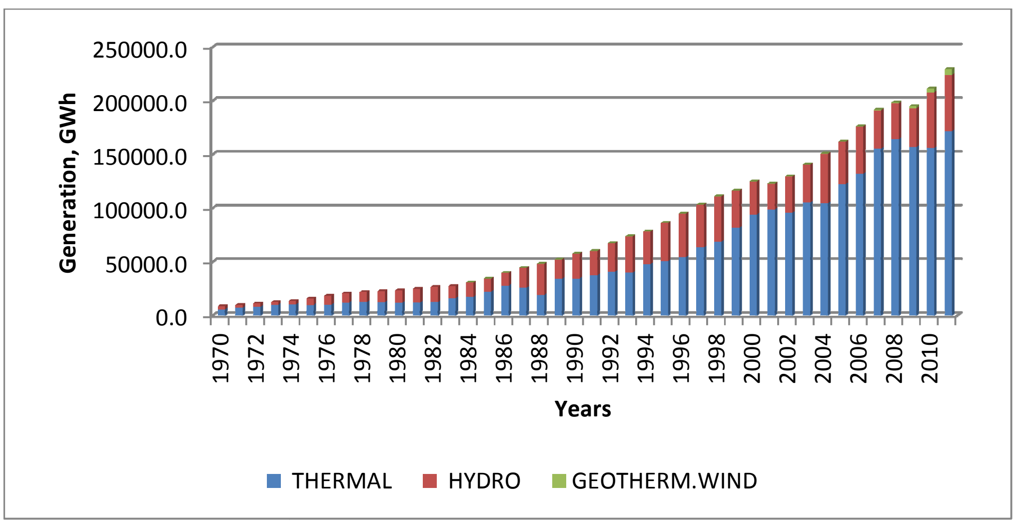


Figure 2.5 The Development of Generation between 1970-2011 by Energy Resources (GWh)

Source: Produced by author using TEİAŞ (2011) data

Distribution Segment: Law No. 4628 states that distribution activities are performed by regional distribution companies based on their licenses. By the implementation of the Strategy Paper issued in 2004 with the High Planning Council Decision No. 2004/3 (dated 17.3.2004), 21 regional distribution monopoly companies were generated and by 18th December 2012, privatization of the 12 distribution regions were completed by the method of operation rights issuance, privatization process of other 8 distribution regions continues. Distribution companies can also obtain retail sales licenses to engage in retail activities. However, by the Decree of EMRB in 2012, the retail sale and distribution activities were aggreed to be performed under the separate legal entities beginning from 2013, January. Distribution companies are responsible for the provision of electricity distribution and connection services to all the users without discrimination, the purchase and provision of ancilliary services, planning investment, performing investments for renewal, replacement, and capacity expansion, preparation of demand forecasts, provision of retail sale services in their service regions for the cases in which there is not any other supplier. In the law, private distribution companies are allowed to engage into the generation activities only if separate accounts are kept; however, in the Draft of Electricity Market Law dated 24 September 2012, activity of the distribution companies is restricted by distribution activity.

Trading Segment: In the trading segment, traders are intermediary between generators and consumers/end-users in the electricity power sales and purchases. Traders are TETAŞ, private wholesale and retail companies, and distribution companies with retail sale licences. However, in the Draft of Electricity Market Law, retail sale and whole sale licenses are combined into an one license type called supply license and also in order to prevent market power, electricity supplied by the affiliated companies cannot exceed the 20% of country-wide total electricity supplied. The parties involved from the consumers side are defined by the Law as eligible and non-eligible consumers. In the Law, eligible consumer is defined as "any real person or legal entity that has the liberty to choose its supplier, due to its consumption of more electricity than the amount set by the Board and/or its direct connection to the transmission system" (EML, 2001, Article 1). Eligibility limit for the year 2012 was set at 25.000 kWh/annual by the Energy Market Regulatory Board and has been reduced gradually since 2002. On the other hand, non-eligible consumers are allowed to purchase electricity from only retail sale companies or distribution companies with retail sale license. In the generation segment, we have explained the participants above. Before examining the relations between traders and the participants in the generation segment and consumers, we define the legal entities involved in wholesale and retail activities as below;

- Wholesale Company is "any legal entity engaged in the wholesale, import, export, trade of electricity energy and/or capacity and the sale of the same to the eligible consumers" (EML, 2001, Article 1). According to Law, wholesale activities can be performed by Turkish Electricity Trading and Contracting Co. Inc. (TETAŞ) and private sector wholesale companies. TETAŞ was formed after the vertical unbundling of TEAŞ and is responsible for the meeting of financial and legal duties for previously signed BO, BOT, and TOOR agreements. TETAŞ buys the electricity generated by EÜAŞ and plants under BO, BOT, and TOOR contracts with bilateral agreements and sells to TEDAŞ, distribution companies or eligible consumers. Bilateral agreements are defined to be "commercial agreements between real persons and legal entities for the purchase and/or sale of electricity under the provisions of civil law without requiring Board approval" (EML, 2001, Article 1). Under the conditions mentioned in the Law, TETAŞ can make energy purchase, import and export agreements. The electrical energy amount to be sold by private wholesale company is restricted by the ten percent of the total electricity consumed in the previous year.
- Retail Sale Company is "any legal entity engaged in the import of electricity and/or capacity and retail sale to consumers, excluding those directly connected to the transmission system, and in providing retail sale services to consumers" (EML, 2001, Article 1). According to Law, retail activities can

be performed by retail sale companies and distribution companies holding retail sale licenses.

Private sector generation companies with generation licenses and autoproducers can sell the electricity to wholesale companies with bilateral aggrements, retail sale companies, distribution companies having retail sale licenses, eligible consumers via bilateral aggrements, balancing and settlement market. The balancing and settlement market has started operation in 2006 in the context of Electricity Market Balancing and Settlement Regulation (EMBSR) issued in 2004 which is cancelled and new regulation was introduced in 2009. Balancing and settlement market under the operation of TEİAŞ complements the bilateral contracts in order to guarantee the balance between supply and demand and “performs the calculation of the amounts payable and receivable due to balancing mechanism and/or energy imbalances and of preparation of the related payable-receivable notices” (EMBSR, 2009, Article 4). Balancing can be performed real-time and day-ahead. Balancing and settlement market works as a pool. Offers and bids are collected by Balancing and Settlement Center and bids are ordered according to the submitted prices from lowest to highest. Price is determined at the level in which all demand is met and this price is applied to all the suppliers. By 1st December 2011, the transition to Day ahead market was performed from Day ahead planning started in 2009. Day ahead market provides engagement into the energy trade for the next day and therefore, balanced system for the next day. Electricity generated by EÜAŞ can be sold to TETAŞ and TEDAŞ via bilateral aggrements; and also EÜAŞ can enter to the balancing market transactions with the excess generation. Electricity generated by private sector plants under BO, BOT, and TOOR contracts are purchased solely by TETAŞ via bilateral aggrements. In the Article 4 of Draft of Electricity Market Law, market operation activity is included into the electricity market activities with a new license type called market operation license. And related to market operation activity, a new market called Organized Wholesale electricity market is defined and this market includes the electricity markets in which wholesale or retail sale of electric power, capacity, or their derivative products are carried out; day-ahead market, intraday market, balancing power market, ancillary services markets, over-the-counter markets and derivative markets under the operation of intermediary legal entity granted by market operation license as Energy Markets Operation Company (EPİAŞ); and balancing power market and ancillary services markets organized and operated by TEİAŞ. Therefore, in the Draft, it is expected that the financial settlement activities performed by Market Financial Settlement Center under TEİAŞ will be carried on by EPİAŞ, in addition, National Load Dispatch Center under TEİAŞ continues its operation as a market operator.

Imports and Exports: According to Law, import and export activities can be performed by TETAŞ, private sector wholesale companies, retail companies and distribution companies holding retail licenses with Board approval. The integration process of Turkish transmission system to ENTSO-E (European Networks of Transmission System Operators for Electricity) system has started by the application of Turkey to UCTE (Union for the Coordination of Transmission of Electricity in Europe) in 2001. There has been many improvements since 2001. By 18th September 2010, Turkish electricity system was connected to ENTSO-E European continent synchronous region and trial operation period has started and continues. Up to now, uncommercial physical bidirectional electricity transaction has been realized between Turkey and Greece, and Bulgaria and limited commercial electricity exchanges are allowed. The Turkey's electricity system integration to Europe are expected to increase the quality and reliability of the electricity supply and provide corporation to improve intelligent network system and energy transaction.

Organized Industrial Zones: Law allows for generation and distribution activites for Organized industrial zones (OIZs) and identifies OIZs as eligible consumers regardless of their consumption level.

The important issues and problems related to the new structure identified in the Law No. 4628 were mentioned by Atiyas and Dutz (2004) and Özkıvrak (2005) as stranded costs and competition in generation and wholesale; transmission and balancing-settlement mechanism; private participation, losses and financial constraints in the distribution; prices and tariffs. By 2011, the total share of EÜAŞ and the Power producers operated under BO, BOT, and TOOR contracts is 68% in the electricity generation. Therefore, state is a dominant player in the generation and wholesale activities which is a threat for market liberalization by deterring new entry to the electricity market. The stranded costs born by the existing BOT, BO, and TOOR contracts are planned to be financed by electricity purchase of TETAŞ from low cost state-owned hydroelectric plants. However the success of this plan depends on wholesale prices and electricity demand realizations. According to Atılgan (2009), because of high pool prices as a result of low reserve margin, the electricity trading based on bilateral contracts has diminished since the start of balancing and settlement market operations in 2006. And also over the period from 2002 to 2011, electricity transmission losses averages 2.4% near to its rate of 2.8% in 2001. Transmission and distribution losses needs to be reduced to the level acceptable according to the international norms. On the other hand, "the distribution sector suffers from growing operating revenue deficits, in turn driven by electricity illicit utilization and non-payment with large regional variation, technical losses, and free or un-billed electricity supply" (Atiyas and Dutz, 2004: 17).

Another problem as mentioned above, in Turkey is the high illicit utilization and losses. Figures 2.8, 2.9 and 2.10 illustrate the illicit utilization and loss ratio over years, the distribution of illicit utilization and loss amount across provinces in 2010, and illicit utilization and loss ratios of provinces in 2010. Illicit utilization and loss ratio has shown an increasing trend up to 2000 reaching 21.6% in 2001; afterwards it has started to decline and reached a minimum level of 14.4% in 2008, is still high when compared to developed countries; however, increasing trend has continued since 2008. In 2010, the illicit utilization and loss ratio was 18.6%. In developed countries, illicit utilization and loss ratio is realized at around 8%-10%, but in Turkey, it was not be lower than 14.4% over the period from 1994 to 2010. "Illicit utilization-losses constitute 20% of total cost of electricity in Turkey which reaches approximately $2 billion amount annually (roughly 1% of Turkish GDP)" (Gümüşdere, 2004: 8). Figure 2.9 and Figure 2.10 demonstrate that the highest illicit utilization and losses and ratios occurred in South-East and East regions of Turkey. In order to reduce illicit utilization and losses, Law No. 4628 propose cost-based pricing system; however, by the implementation of national tariff system as a result of Law No. 5496, tariffs become an ineffective tool to encourage the distribution companies for the reduction of illicit utilization and losses. In order to eliminate the efficiency costs caused by regional cross-subsidization and considering socio-economic dimensions and also financial sustainability of privatized distribution companies, Gümüşdere (2004) suggested the provision of direct subsidies financed by the imposition of taxes on the electricity consumption if electricity consumption is price inelastic.

Another important issue is pricing and tariffs. "Tariff is a regulation of revenue and pricing among consumers, producers and other third persons. It regards all parts' rights" (Gümüşdere, 2004: 15). Before Law No. 4628, integrated tariff structure was implemented. By Law No. 4628, in line with the vertical unbundling of the sector, EMRA has unbundled the tariff components according to the license type, i.e., generation, transmission, distribution, retail sale. The prices in the generation segment is unregulated and determined by bilateral aggrements or spot market price in the balancing market, however, tariff of TETAŞ is under the regulation of EMRA due to the presence of purchase guaranteed generation companies according to Law No. 3096. Also, tariffs of transmission, distribution and retail sale are regulated by EMRA. By Law No. 5496 issued in 2005, national tariff system has been implemented based on price balancing mechanism across regions and allowed for cross-subsidization across distribution regions; however, this application is in contrast with the electricity market law.

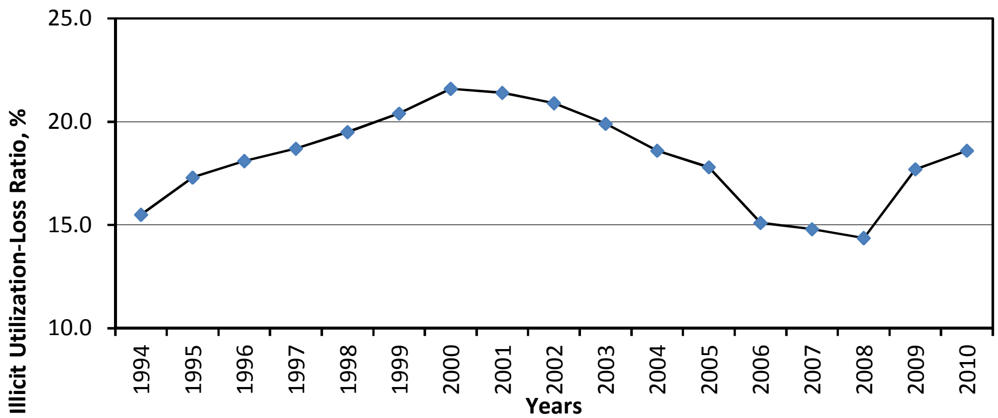


Figure 2.6 The Development of Illicit Utilization and Loss Ratio between 1994 and 2010, (%)

Source: TEDAŞ (2010)

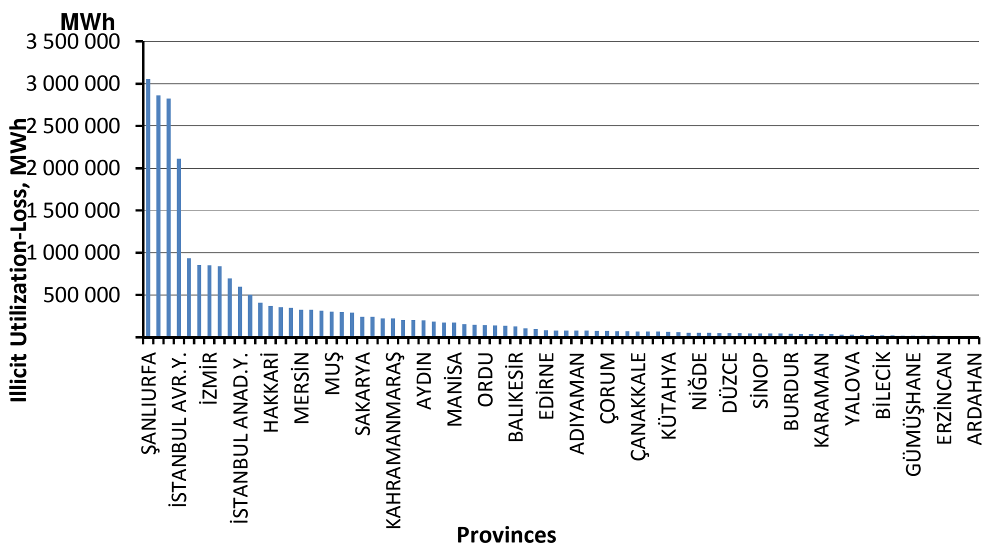


Figure 2.7 The Provincial Distribution of Illicit Utilization and Loss Amounts (MWh)

Source: TEDAŞ (2010)

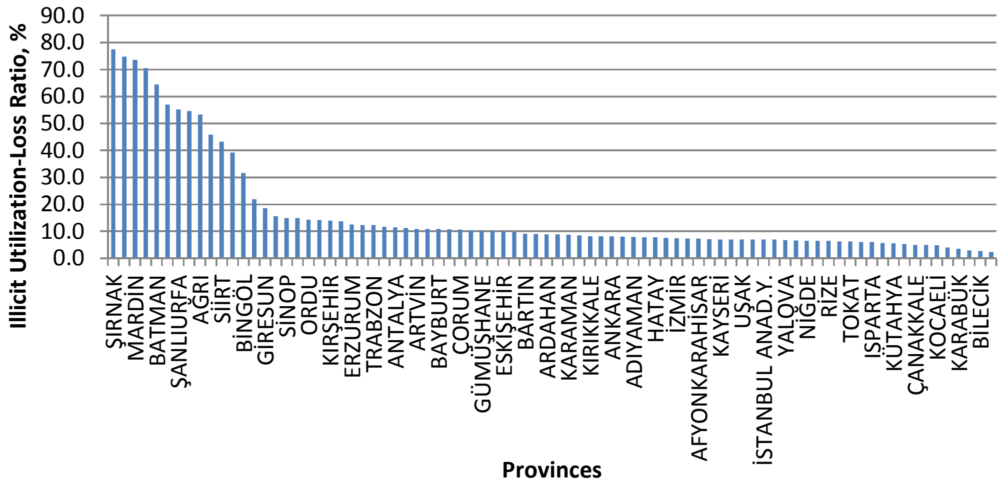


Figure 2.8 The Illicit Utilization and Loss Ratio by Province in 2010 (%)

Source: Produced by author using data from TEDAŞ (2010) statistics

"It applies almost same tariffs across regions and consumption purposes through cross subsidies, meaning that low cost consumers subsidize high cost ones causing a single final price" (Gümüşdere, 2004: 16). According to the Draft of Electricity Market Law, this implementation continue until 2015. This mechanism was firstly introduced in Strategy Paper 2004 and Strategy Paper 2009 mentioned the continuation of this mechanism until the end of the transition period. Strategy Paper 2009 also pointed out that the energy pricing will be cost-based and implementation of cost-based pricing mechanism introduced in 2008 will be continued. "Although this cost based and subsidy supported mechanism is in operation, the Electricity Market Law of 2001 propose a different mechanism that prohibits cross subsidies and sets caps for revenues and prices" (Gümüşdere, 2004: 18) and moreover, according to the Electricity Market Law, "in cases where consumers in certain regions and/or in line with certain objectives need to be supported, such subsidy is provided in the form of direct cash refunds to consumers without affecting the prices" (Özkıvrak, 2005: 1345). As a demand-side management tool, time-of-use pricing has been implemented by TEDAŞ based on the preference of customer for all customer classes. Customers can also choose between two block and one block pricing schemes. For more detailed information on tariffs, one can refer to Doğan (2012). Figures 2.6 and 2.7 show the comparison of electricity prices across selected OECD countries for the year 2010. In the figures, as the electricity prices for U.S. exclude taxes, comparison with other countries is not suitable, therefore while calculating the average electricity prices over the countries, we exclude U.S. electricity prices. The lowest prices for industrial and second lowest price for residential sectors are applied in Canada as their electricity generation is highly dependent on hydroelectric plants. On the other hand, Turkey is one of the four countries that implements the higher electricity prices to industrial sector. While the industrial sector electricity prices in Turkey is higher than the average industrial electricity price across the countries, just the opposite is observed for the residential sector. In Turkey also, the small difference between residential and industrial electricity prices is the indication of cross-subsidization between sectors, in our case from industry to residents.

Up to here, we examine mostly the supply side of the electricity market. However, demand side of the market should also be analyzed. From Figure 2.13, we observe that high economic growth is associated with high electricity consumption growth. During the domestic economic crises in 1978, 1980, 1986, 1989, 1991, 1994, 1999, and 2001 and after the external shocks like petroleum shock of year 1979, gulf war in 1990, crises in emerging countries in 1990s, and World Economic crisis of year 2008, economic growth and electricity consumption growth dropped tremendously. Over the period from 1975 to 2010, electricity consumption increases on average at a rate of 8%, annually. Figure 2.11 demonstrates that the highest share of the industrial sector in the total electricity consumption has continued since 1970s and in 2010 its share is 46.1% declining from the percentage share of 64.2 in 1970, however, the share of residential sector has increased rapidly from 14.5% to 24.1% as a results of increase in living standards as well as the increase of electrification in all around the country.

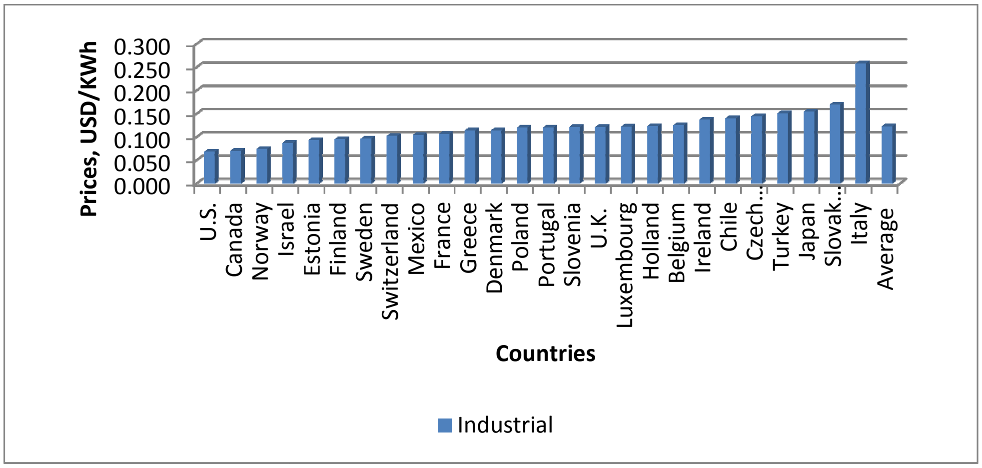


Figure 2.9 Industrial Electricity Prices for Selected OECD Countries for the Year 2010, USD/KWh

Source: Produced by author using data from IEA STATISTICS - Electricity Information 2011

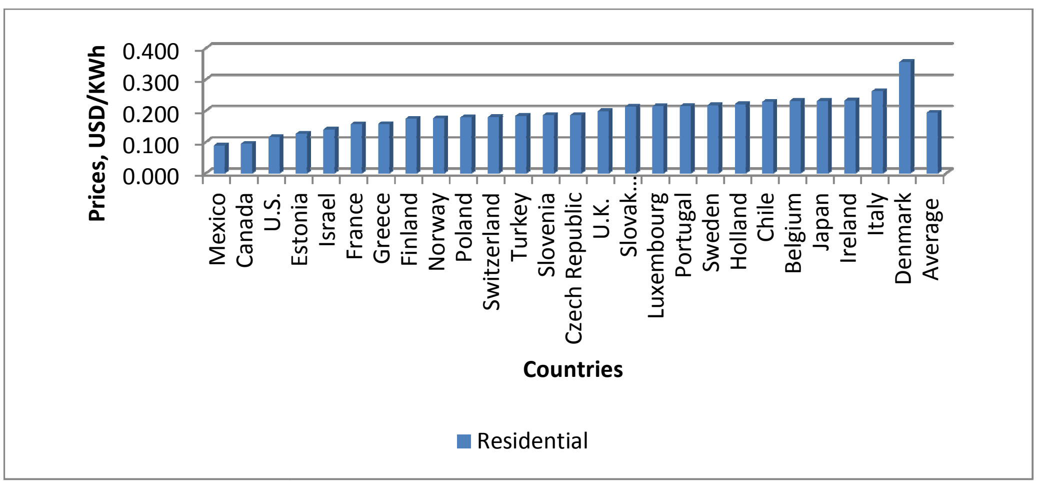


Figure 2.10 Residential Electricity Prices for Selected OECD Countries for the Year 2010, USD/KWh

Source: Produced by author using data from IEA STATISTICS – Electricity Information 2011

In 2010, the share of industrial sector is 46% followed by residential sector with a share of 24% in the total electricity consumption (see Figure 2.12).

The beginning of the problems related to supply and demand balance dates back to the 1970s. Because of the lack of investments in the electricity sector to meet the electricity demand, the first planned power cuts began in 1973. As a result of 1970's oil crises, implementation of studies on energy efficiency has become popular in all around the world. In Turkey, "planned energy conservation activities were first implemented in 1981 by the General Directorate of Electrical Power Resources Survey Administration (EIEI). Since 1981, EIE has been conducting these activities" (Hepbaşlı and Özalp, 2003: 231). Legal basis of energy efficiency activities was formed by the enactment of Energy efficiency Law No. 5627 in 2007. Figure 2.14 and 15 show the projections of 10-year generation capacity performed by TEİAŞ (2012). In capacity projections, low and high electricity demand forecasts have been obtained from MNER. By considering the existing plants, public and private plants under construction, and the power plants granted by license and expected to be in operation at unknown dates, the capacity projections were done under two scenarios on the expected installed, reliable and projected generation capacity based on the progress report of EMRA prepared on January, 2012 about the power plants (granted by license) expected to be in operation at unknown dates over the projection period. If we ignore the uncertain capacity additions and assuming that the plants under construction will be in operation in the expected dates, reliable generation capacity will be insufficient to meet the energy demand in 2017 and 2019 under high and low demand assumptions, respectively; on the other hand, installed capacity seems to be sufficient to meet the peak demand. Therefore, it is crucial to accelerate the investments on new capacity additions. Because of long lead times for the power plants, planning becomes much more important in the investment on new power plants. For such a planning, reliable demand projections are needed.

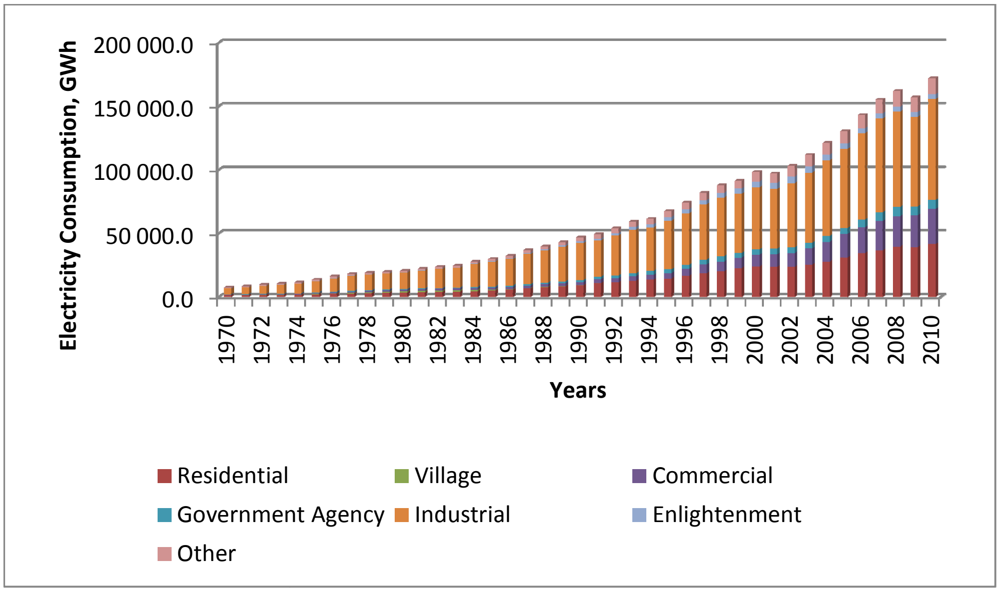


Figure 2.11 The Development of Electricity Consumption's Sectoral Distribution between 1970 and 2010 (GWh)

Source: Produced by author using data from TEDAŞ (2010) statistics

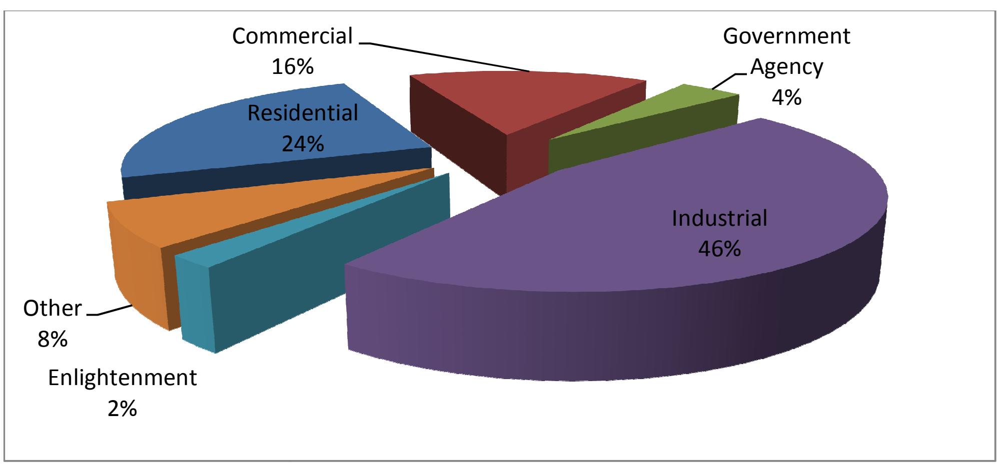


Figure 2.12 The Sectoral Shares of Electricity Consumption for Year 2010 (%)

Source: Produced by author using data from TEDAŞ (2010) statistics

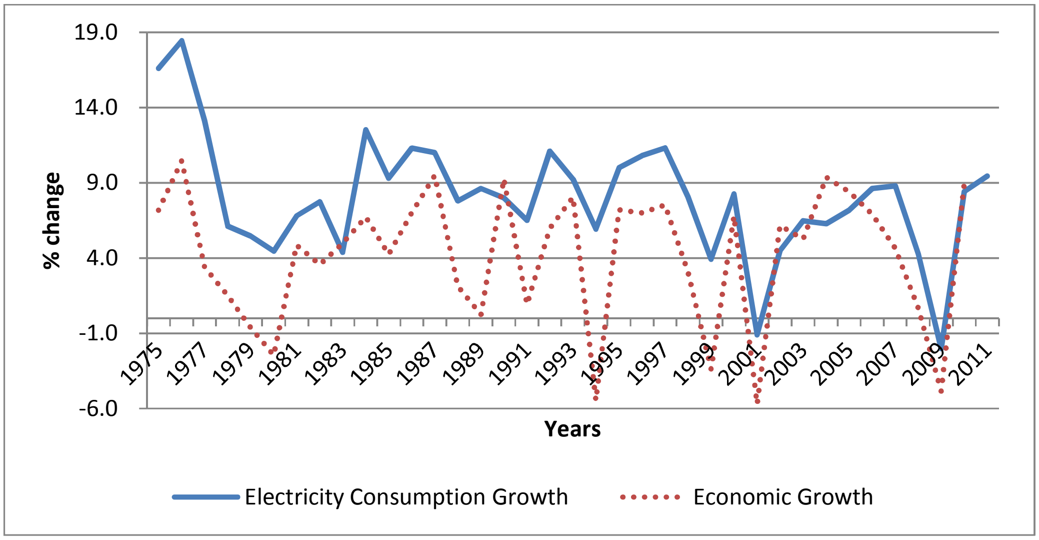


Figure 2.13 The Development of Gross Electricity Consumption* Increase between 1975 and 2011 and Economic Growth between 1975 and 2010 (%)**

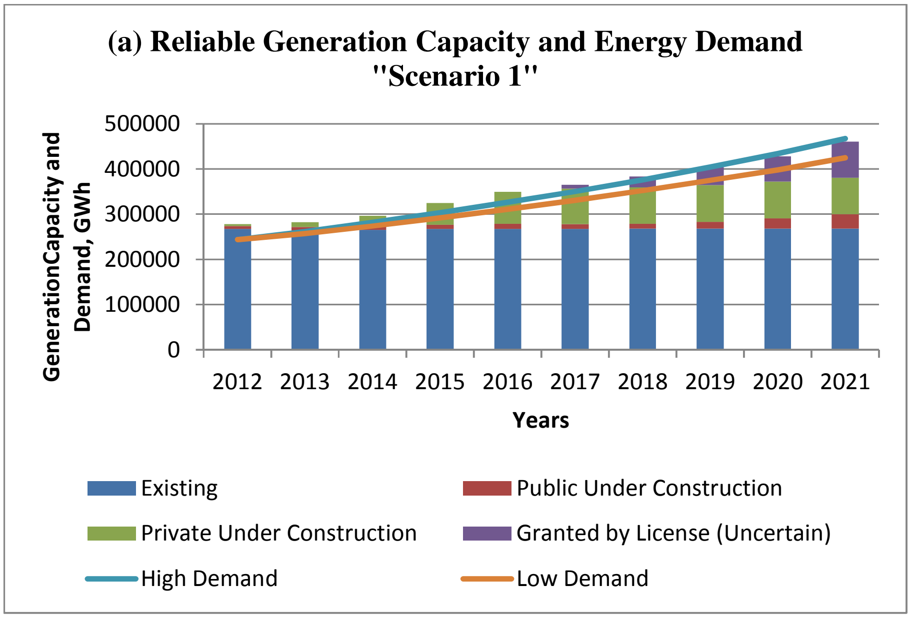
Source: Produced by author using data from TEİAŞ (2011) and DPT statistics

Note: *Gross Demand=Electricity Requirement=Apparent Consumption=Gross Generation+Import-Export

**Percentage change in harmonized gross domestic product by TURKSTAT data at 1998 prices

Among many other studies, Erdoğdu (2007), Ediger and Tatlıdil (2002), Madlener et al. (2005), Hamzaçebi (2006), and Akay and Atak (2006), have critized the MENR's projections based on Model for Analysis of Energy Demand (MAED) module of Energy and Power Evaluation Program (ENPEP) as it overestimates electricity demand.

While analyzing the electricity sector, we need to consider environmental issues as energy sector is one of the major contributor to the environmental deterioration by, among others, emitting Greenhouse gases and causing climate change; leaving high pollutants to the water and the soil during cooling processes of plants, drilling oil, and mining coal; generating acid rains as a result of sulfur dioxide (SO_2) and nitrogen oxide (NO_x) emissions, radiation leakage and wastes from nuclear plants after accidents. In order to mitigate these environmental damages, some domestic legal regulations to encourage the energy efficiency applications and power plants utilizing renewable resources were introduced. Moreover, on the international level, Kyoto protocol was signed in 1997 and came into force in 2005. As a part of United Nations Framework Convention on Climate Change (UNFCCC), Kyoto protocol is an important step to increase the awareness about the causes and results of climate change, and to decrease emissions by putting emission targets; besides it proposes some mechanisms to mitigate the emissions such as emissions trading (the carbon market), clean development mechanism (CDM), joint implementation (JI). For further information on each mechanism, one can refer to the website of the UNFCCC (http://unfccc.int/kyoto_protocol/items/2830.php). The industrialized countries under Kyoto protocol have aggreed to reduce their emissions level to 1990's level for the period from 2008 to 2012; however, the commitment period of Kyoto protocol was extended to the period between 2013 and 2020 in 2012 at Doha Climate Change Conference. "The Kyoto protocol was ratified by Turkish Parliament in February 2009, which is expected to lead to the introduction of legally compulsory commitments for the reduction of greenhouse gases" (Dilaver and Hunt, 2011: 436). But, Turkey does not declare any emission target. Dilaver and Hunt (2011) have mentioned that in the future, in order to satisfy the requirements of Kyoto protocol, in Turkey, the implementation of carbon taxes and incentives for the utilization of renewable energy resources can cause increase in the end-use electricity prices, however, which can be decreased by efficiency improvements in the electricity generation. In this regard, Turkish Ministry of Environment and Forestry has prepared a National Climate Change Strategy Paper in 2010 which defines the measures and required works to be implemented in the related sectors against the climate change covering the 11 year period.



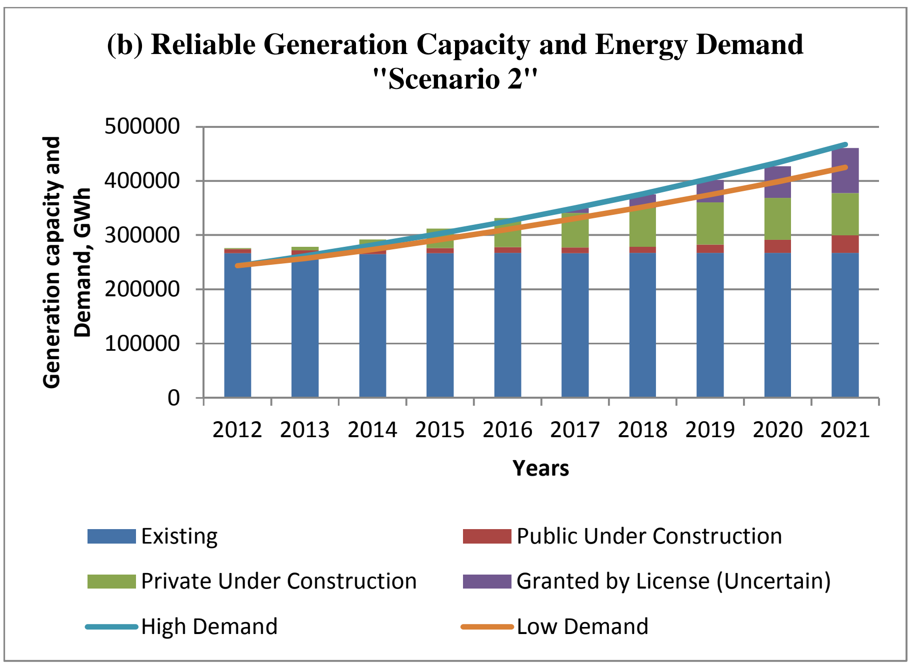
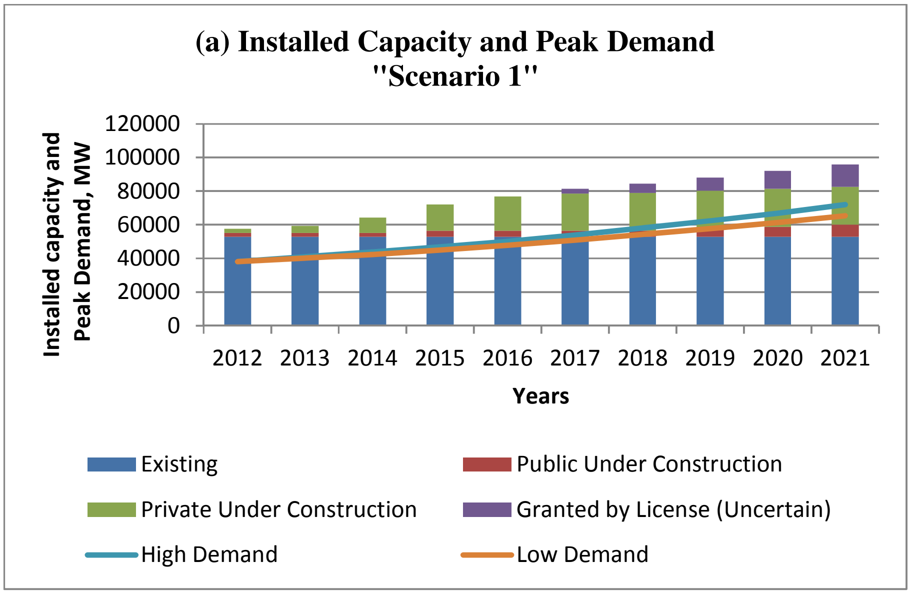


Figure 2.14 The Reliable Generation Capacity and Energy Demand Projections under Scenario 1, Scenario 2, and the Assumptions of High and Low Demand over the Period from 2012 to 2021

Source: Reproduced by author using TEİAŞ (2012) projections



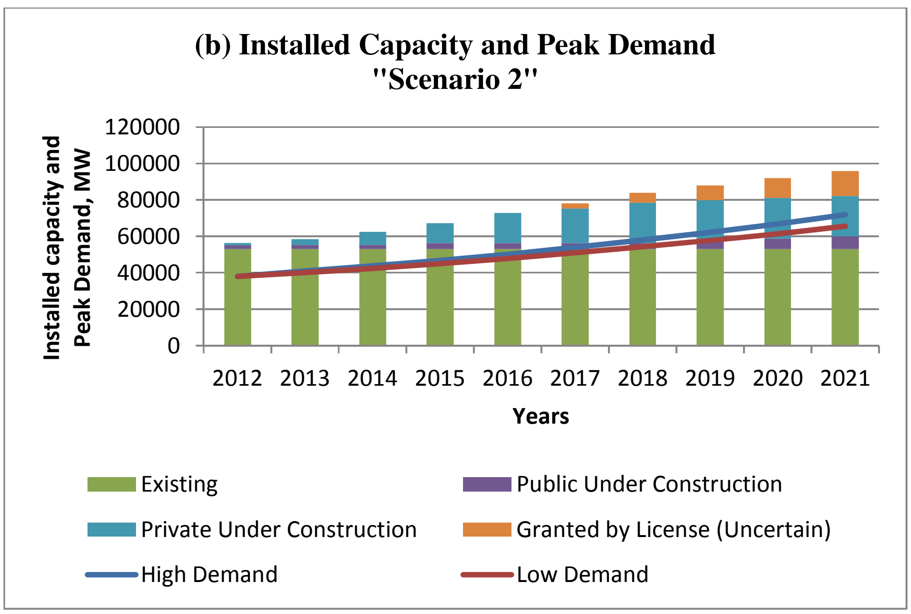


Figure 2.15 Installed Capacity and Peak Demand Projections under Scenario 1, Scenario 2, and the Assumptions of High and Low Demand over the Period from 2012 to 2021

Source: Reproduced by author using TEİAŞ (2012) projections

According this paper, the short, medium, and long term measures for the controlling the Greenhouse gas emissions in the energy sector are basically based on the energy efficiency applications and the utilization of low/zero emission technologies, like renewable energy, nuclear, hydro, and clean coal technologies. In the energy sector, the target limit for carbondioxide emission was set at 7% according to the reference scenario until 2020.

In this study, as our main concern is the consumption side of the electricity market, next section provides brief review of literature on the econometric studies of the electricity demand.

CHAPTER 3

LITERATURE REVIEW

"Electricity would remain little more than an intellectual curiosity for millennia until 1600, when the English scientist William Gilbert made a careful study of electricity and magnetism" (Stewart, 2001: 50) and the English word "electricity" stemmed from Gilbert's use of new Latin word "electricus" (Baigrie, 2006; Chalmers, 1937). Later on, in 1752, Benjamin Franklin showed that lightning was electrical in nature in his experiment (Uman, 1987). By the invention of electric motors in 1821 by Michael Faraday, bulb in 1879 by Thomas Edison, and many progresses in 19th century, electricity has become important tool for industrialization and modern life.

The planning for supply and demand of energy is very important for the well-planned development of the energy sector and for future energy policies. Therefore, constructing suitable energy models gain very much attention in the literature especially after energy crises. Charpentier (1975) reviewed the characteristics of some of the energy models used by different countries in his study. More recently, Bhattacharyya and Timilsina (2009) have compared different energy demand models. On the other hand, for Turkey, as stated by Erdoğdu (2007), since 1984, MNER has been employing simulation model "Model for Analysis of Energy Demand" (MAED) and Wien Automatic System Planning (WASP) developed by International Atomic Energy Agency (IAEA) to determine general energy and electricity demands and obtain electricity generation plan. The electricity demand projections are performed under base and low scenarios based on growth targets given by State Planning Office (SPO). Akay and Atak (2006) defined MAED as a simulation model developed for evaluating medium and long-term demand for energy which uses bottom-up methodology and they critized the model as one needs too much input data and also experimental knowledge to run the model. TEİAŞ

(2003, 2004, 2005, 2006, 2007 and 2008) employs the Base and low demand series calculated with MAED model by MENR to obtain Turkish Electrical Energy 10-Year Generation Capacity Projections using WASP Generation and Investment Optimization Model. Charpentier (1975) in his study summarized the characteristics of WASP model developed by IAEA. But as discussed and mentioned in Erdoğdu (2007), Ediger and Tatlıdil (2002), Madlener et al. (2005), Hamzaçebi (2006), and Akay and Atak (2006), MNER's projections have overestimated electricity demand because of the effects of government policies on the results due to the use of target values of SPO in the projections.

In our study, we focus on electricity demand models and our aim is to analyze the factors affecting total electricity demand and obtain price and income elasticities of electricity demand. In the empirical literature, some studies have analyzed the aggregate electricity demand without sectoral disaggregation. Pouris (1987) claimed that in order to obtain the elasticity estimates for the entire economy from the sectoral analyses, taking the weighted average of the elasticities of all the individual sectors will give downward biased elasticities for the total economy, as, some hidden interactions among the different sectors may not be observed in the sectoral analysis. Also, another important point noticed by Pouris (1987) is such that more stable relationships can be obtained by the higher aggregation level. By taking into account these two remarks, we prefer to study at the aggregate level in order to obtain elasticity estimates for the entire economy.

In this section in line with our study, we review the studies which analyzed the factors affecting total electricity demand for Turkey and other countries; therefore we restrict our attention to the econometric studies, only. For the discussion on electricity demand forecasting, Rhys (1984), Stoll (1989), Fisher et al. (1992), Toptaş (1992), Şahin (1993), Gellings (1996), Cullen (1999), Mehra and Bharadwaj (2000), and Feinberg and Genethliou (2005) have provided an account of brief description of methods that have been employed in the literature and industry. Table 3.1 summarizes the various studies and gives brief information on time period and method employed, countries studied and income and price elasticities obtained. Studies significantly differ according to the data frame, models and methods employed and exogenous variables incorporated. As observed by Dahl (1993), there is a significant improvement over the modeling approaches, estimation techniques and functional forms over time. However, Bohi and Zimmerman (1984), Dahl (1993), and Heshmati (2012) have noticed that the preferences over the models, estimation techniques, and data type are primarily based on the purpose of the study, availability of data, and available computational techniques. According to Heshmati (2012) and Bendezu and Gallardo (2006), electricity demand studies can be categorized based on aggregation level such that aggregate national, semi-aggregate (sectoral and regional), and disaggregate (household and firm) levels and this categorization will determine the type of data required, model specification, and estimation method. In order to see how the models and techniques evolve over time, we prefer to present the literature review of the studies ordered according to the publication year in the Table 3.1. Dahl (1993) and Al-Faris (2002) have noticed the improvement of the modeling approaches, functional forms, and econometric techniques over the past two decades leading to more reliable elasticities and we can observe this situation from the Table 3.1. Taylor (1975) presented a detailed survey on the major empirical electricity demand studies between the years 1951 and 1973. Other reviews can be found in the studies of Pachauri (1975), Bohi and Zimmerman (1984), Bates and Moore (1992), Fisher et al. (1992), Dahl (1993), Madlener (1996), Dahl and Roman (2004), Kriström (2008), Yépez-García et al. (2011), and Heshmati (2012). Dahl (1993) analyzed the surveys of Taylor (1975), Taylor (1977), Bohi (1981), Kirby (1983), and Bohi and Zimmerman (1984). Recently, Khanna and Rao (2009) have reviewed the literature on econometric electricity demand studies between 1984 and 2008 for the developing countries. Moreover, Dahl (2011) provided an analysis of more than 450 studies on nearly 60 countries published between the years 1951 and 2008. The main issues discussed in the electricity demand literature were identified by Heshmati (2012) as endogeneity of electricity prices, functional form, nonlinearity, specification, estimation and type of data. Heshmati (2012) gave detailed information about each, also the previous surveys have focused on these points along with the discussions on which price, marginal or average, to use and aggregation level of the data.

We first start by reviewing the survey studies in order to understand the issues that need attention and continue with the analysis of some of the recent total electricity demand studies. However, our review does not include the studies that have analyzed time of day demand and pricing and also other dynamic pricing schemes. Some of the studies on time of day demand and dynamic pricing schemes include the analysis by Cargill and Meyer (1971), Hausman et al. (1979), Hawdon (1992), King and Shatrawka (1994), Filippini (1995), Patrick and Wolak (1997), Cullen (1999), Faruqui and George (2005), Taylor et al. (2005) and more recently, by Fan and Hyndman (2011), Filippini (2011), di Cosmo et al. (2012). We only focus on linear models. However, if there are asymmetries in electricity demand, Narayan and Popp (2009) have argued that these models can be misleading for policy making purposes because of invalid forecasts obtained using them and also assumptions of some tests will not be satisfied, thus the results of these tests will not be reliable. Asymmetries in electricity demand was also analyzed recently by Lee and Chiu (2011) for OECD countries over the period from 1978 to 2004 employing panel smooth transition regression model. The model explained the per capita electricity consumption by the following variables such as per capita real GDP, real electricity price, and temperature; and it was estimated with instrumental variable approach to account for possible endogeneities using different threshold variables. They have found evidence of nonlinearity in the electricity demand relation and also that electricity demand is inelastic with respect to income, own-price and temperature. The findings of the study further showed the gradual decline in income elasticity and gradual increase in temperature elasticity over the time period studied.

In Section 3.1, we present the previous surveys and the general problems considered in the studies under consideration. Section 3.2 reviews the electricity demand studies for Turkey. In Section 3.3, we present the findings of some electricity demand studies for other countries by classifying according to the data type, such that, panel data, time series data, cross section data.

3.1. Previous Surveys on the Electricity Demand Studies

During the 1950s, economists were interested in developing empirical estimates of the demand functions for all consumer goods, individually or in systems that satisfied the constraints of demand theory and electric power is one such good (Fisher et al., 1992: 120). The earliest work analyzing the electricity demand is Houthakker (1951)'s study on residential sector which used the cross-sectional data on 42 provincial towns of United Kingdom over the period from 1937 to 1938. He considered two-part tariff structure and found significant effects of income, electricity price, gas price, and stock of heavy domestic equipment on electricity consumption. According to Fisher et al. (1992), Houthakker (1951) has treated electricity as any other consumer good in his analysis.

Taylor (1975), in his survey, gave detailed information on the studies of Houthakker (1951), Fisher and Kaysen (1962), Houthakker and Taylor (1970), Baxter and Rees (1968), Wilson (1971), Cargill and Meyer (1971), Anderson (1971), Mount, Chapman, and Tyrell (1973), Anderson (1973a), Lyman (1973), Houthakker, Verleger, and Sheehan (1973). For another criticism of Mount, Chapman, and Tyrell (1973)'s study in the context of methodological issues, one can refer to Mayer (1980) who compared the exploratory methods versus confirmatory approaches. From the findings of these studies, Taylor (1975) observed that the long run price and income elasticities of demand are larger in magnitude than the short run ones, and demand is elastic with respect to price in the long run such that long run price elasticity lies between -1 and -2, however, he could not reach a general conclusion about the long run income elasticity as one study has found a negative elasticity and the others between 0 and 2. For the cross-price elasticities, he inferred from the results that in the short run, they are insignificant; but in the long run, although there is not a clear direction in the relation, there is evidence of relation between electricity demand and prices of other energy types. On the other hand, according to Taylor (1975), in the literature, seasonal variation in demand, demand by time of day, and especially in the industrial sector, distinction between long run and short run demand was overlooked. Further, he critized the previous studies as they did not account for decreasing block pricing structure causing biased estimates of coefficients and recommended the inclusion of average price along with the marginal price. However, Nordin (1976) showed that it was not appropriate to use average price, instead a variable representing the lump-sum payment made by the customer before buying additional units at the marginal price must be used. Francisco (1988) proposed two electricity demand models in which one included Taylor's specification of inframarginal price, while other used the Nordin's approach. He concluded that Nordin's specification of inframarginal price variable produced theoretically compatible results. In other study, Berndt (1978) emphasized and established that the exclusion of average price from the model caused only negligible biases employing Houthakker (1951)'s data and model with some revisions. Meyer (1979), also estimated electricity demand models employing both marginal and average electricity prices and he observed that although the coefficient of marginal price was not significant, the inclusion of marginal price influenced the coefficients on average price and other variables. Shin (1985) found supportive empirical results for the claim of the response of consumers to the perceived average prices from the electricity bills. As the decreasing block pricing leading price dependent on quantity consumed produces the simultaneity problem, Halvorsen (1975) built an equation system constituted of demand and price equations. By using double logarithmic form, he demonstrated that no difference in the results will emerge using either marginal or average price. Baron and Lusky (1975), Wilder and Willenborg (1975), Jakob (1976), Halvorsen (1976), and Meyer (1978) have employed the variants of Halvorsen (1975)'s model. Espey and Espey (2004), in their meta-analysis, have found that price elasticity estimates from studies used marginal price are smaller than the ones using average prices in the short run, however, in the long run; there is not any significant difference between them.

Other comprehensive survey is provided by Bohi and Zimmerman (1984) analyzing the studies between 1978 and 1983. They have classified the studies according to the sectors first as residential, commercial, and industrial sectors; then by model types which are structural form, reduced-form end use, reduced-form static, and reduced-form dynamic models; and further by the type of data as aggregate or disaggregate; and by whether marginal or average price variable was used. From the group of studies based on reduced-form static models for the residential sector, they have concluded that long-run price elasticity was around 0.60, while, long-run income elasticity was less than 0.20. As an overall conclusion based on the various types of studies reviewed, they have obtained a consensus estimate for price elasticity for residential sector as near 0.2 and 0.7, in the short run and long run, respectively. For the commercial and industrial sector, such a consensus estimate could not have been reported, however, they have observed that commercial and industrial demand are more elastic than the residential demand. Other observations they have noticed are the evidence of the inverse relation between price and income elasticities across different models and no impact of energy crisis on the structural characteristics of demand through the economic determinants. Bohi and Zimmerman (1984) have focused on the importance of modeling issues and data for the differences between the results of various studies. According to them, choices related to model type, level of data aggregation, functional form, estimation technique, assumptions on supply, and measurement issues are highly dependent on the objective of the study and the data availability. The studies have been compared based on these characteristics and they have found that although structural model shows better performance, static reduced-form models also perform well when disaggregated data is used; however static reduced-form models can produce high long run elasticities in the case of aggregated data. Also, noticed by Bohi (1981), they have observed that dynamic reduced form models can give unreliable elasticity estimates. For the aggregation level of data, there are different views. McRae and Webster (1982) have found that different data arrangement methods lead different parameter estimates. Bohi and Zimmerman (1984) have considered the results obtained from the studies that have used disaggregated data as more reliable. This is also supported by Berg (1975), Hartman and Werth (1979), Green et al. (1986), Westley (1989a), Bernard et al. (1996), and Chakir et al. (2003). Berg (1975) showed that the estimations of price elasticity can be affected by the composition of demand under the declining block pricing structure and emphasized on the importance of micro level data for better analysis of electricity demand. The benefits of regional disaggregation were discussed by Westley (1989a) as the increase in the number of observations and variation, in addition, decline of collinearity in the data. Hartman and Werth (1979) claimed that better estimates are obtained as the disaggregation level increases. In addition, Bernard et al. (1996) have discussed the possibility of biases in the estimates of price and income elasticities due to the high aggregation level of the data. Chakir et al. (2003) have critized the studies using aggregate level data as price responsiveness of demand is smoothed. On the other hand, Pouris (1987) mentioned that more stable relations could be obtained by higher level of aggregation. Also, Beierlein et al. (1981) argued the comparative advantage of study on aggregate units over the individual units for the policy purposes. Due to the expensiveness or unavailability of the micro level data, Hartman (1982, 1983) preferred to use aggregate level data in his empirical study. Lastly, Bohi and Zimmerman (1984) have stated that price of substitutes are usually insignificant or small as a results of partial equilibrium characteristics of the models employed and price elasticity estimates does not show any simultaneity bias.

Besides the previous surveys, Dahl (1993) surveyed the U.S. electricity demand studies between 1981 and 1992. She stratified the studies first according to sectors, and then substratified according to the aggregation level of the data, type of data, and subsectors. Studies reviewed have made interesting contributions to the electricity demand literature by considering many important issues, for example, the seasonal variation in the electricity demand (Archibald et al. (1982)), rural regional electricity demand (Maddigan et al. (1983)), structural changes in demand elasticities (Chern and Bouis (1988), and Dunstan and Schmidt (1988)), importance of functional form (Chang and Hsing (1991)), effects of aggregation level (Green et al. (1986)), and specification of dynamics (Kolstad and Lee (1992)). Among these studies, Green et al. (1986) have observed that the long run price elasticity ranges from -0.44 to -2.10 clustering around -1.40 according to the results of previous empirical studies for the residential sector. They have claimed this wide range of estimates is as a result of aggregation level. Chang and Hsing (1991) have focused on the importance of functional form and in their application, determined the functional form based on the data using Box-Cox transformation. They have found that arbitrary use of double-log or linear functions for the electricity demand relation can cause misleading results for the patterns of estimated elasticities. Their result was also supported by Munley et al. (1990). Xiao et al. (2007) have also compared different functional forms for electricity demand model following a Bayesian approach. They have employed Deviance Information Criterion and found that among functional forms as linear, log-linear, translog share, and Almost Ideal Demand System, last two specifications perform better for US household electricity demand. The findings of Kolstad and Lee (1992) have shown the importance of appropriate specification of dynamics as, the misspecified dynamics can cause dramatic errors in the estimation of demand elasticities. Dahl (1993) noticed the wide variation of elasticity estimates across studies. But she reached some general conclusions. The observations made are that studies on cross-sectional data produced more elastic response than the ones using time series data; the residential electricity demand studies based on disaggregated data have found inelastic price and income response and also, lower income elasticities compared to studies employing aggregate data. Moreover, she noticed that aggregate data studies have found a reduction in income elasticities after 1974 and also long run price elasticity near -1. For the residential sector, based on the results of previous studies, she claimed that electricity demand is inelastic with respect to price and income and dynamic models produced erratic elasticity estimates. Whereas, from the findings of the studies on commercial and industrial sectors, she inferred that for these sectors, in the long run electricity demand is price elastic and income inelastic, however there is considerable variations in elasticity estimates across industries, and also price elasticity have dropped after 1973.

Another review on energy (mainly electricity) demand studies was provided by Madlener (1996). The attention in this survey was restricted to the residential sector econometric studies. The studies were categorized into eight groups based on the following approaches: log-linear functional forms, transcendental logarithmic functional forms, models of qualitative choice, household production theory, pooled cross-section time series models, cointegration analysis, general-to-specific modeling, and asymmetric models. One can refer to Table 1 in the survey for the advantages and disadvantages of each approach.

Espey and Espey (2004) have performed meta-analysis in order to understand the differences in the elasticity estimates of various residential electricity demand studies. In their model, short run/long run price and income elasticities were explained as a function of the factors such as data characteristics, model structure, estimation technique, and time and location of the study. They have estimated both semilog and gamma model by GLS and MLH estimation methods, respectively. Their data set contains information on 36 studies over the period from 1971 to 2000. Short run (long run) price elasticities ranged from -2.01 to -0.004 (-2.25 to -0.04) with a mean -0.35 (-0.85); whereas, short run and long run income elasticities were in the ranges of (0.02 to 5.74) and (0.04 to 3.48) with a means of 0.97 and 0.28, respectively. Double log, static, reduced form OLS model using annual cross-section time series data for the aggregate U.S. and marginal price for electricity were employed as a base model.

Kriström (2008) provided a review of some empirical studies on residential energy demand. He pointed out that key drivers of energy consumption are income and price; and long run price elasticities are larger than short run elasticities due to the time lag of capital stock adjustment. Temperature was mentioned to have important role in determining the energy consumption. He argued that it is still an open question if the socio-economic variables and attitudes such as environmental concerns have significant effects on energy consumption. According to Kriström (2008), different estimation methods, data sets, and aggregation level lead high variation across the results of the studies and make it hard to obtain consensus elasticities. He compared some of the widely employed policy instruments which are energy taxes, energy efficiency standards for appliances, energy labels, energy conservation grants, and thermal efficiency standards and in addition, he mentioned that choice among them is highly related to the objectives of the policy, however, energy taxes is the most efficient.

For developing countries, Khanna and Rao (2009) have reviewed the studies dated back to 1984. Some of the econometric studies were based on aggregate data, while, the others have employed microdata on household level or firm level. They have mentioned that GDP, prices, income, urbanization, seasonal factors, and economic activity characteristics are the main determinants of electricity demand. In the studies analyzed, they have observed the inclusion of real GDP, real electricity price, temperature measures, urbanization, prices and stocks of appliances, prices of other energy sources, lagged electricity consumption to the electricity demand relation. According to Khanna and Rao (2009), the main problem in developing countries is the nature of electricity demand as electricity demand is supply constrained causing frequent electricity outages; and also illicit utilization and losses, subsidies, and captive generation were described as other additional problems. Therefore, the inclusion of price may not be meaningful. On the other hand, in transition economies, due to the overinvestment in capital before the collapse of Soviet Union, electricity consumption may not be restricted by the previous period's capital stock. From the analysis of various studies on aggregate electricity demand, the own-price elasticity of electricity demand was observed to range between -0.85 and -0.04 in the short run and between -1.02 and -0.11 in the long run. Response of electricity demand to changes in income was obtained to be low, both in the short and the long run, but lower in the short run. Another important observation is that industrial and commercial electricity demand was found to be more income/output responsive compared to the residential demand. Socioeconomic (urbanization, industrialization, literacy rate, etc.) and climatic factors were also observed to have significant effects on electricity demand. They have also stated that although these variables have greater impact in high-income countries, country specific factors are influential on the degree of the impact. In the studies, cross-price elasticities were rarely found to be significant with theoretically acceptable signs and they have explained this situation as a result of the limited or impossible interchangeability of energy type for a particular equipment or appliance, thus leading prices of other energy forms to be irrelevant. Other important variable noted is the share of population having access to electricity. For the household level electricity consumption, household characteristics (size, income, and education), dwelling characteristics (size, location and type), weather variables, electricity and other fuel prices, and costs and availability of electrical appliances were expected to be important drivers. The analysis of studies at the household level demonstrated that electricity demand is both price and income inelastic in developing countries. They argued that although this result is also valid for developed countries, estimates of elasticities are found to be higher in the studies on developing countries.

As a summary, most of the studies only analyzed one sector, residential, commercial, industrial, and other; while some others studied all the sectors and compared the elasticities. There are also studies at aggregate level without differentiating between the sectors. This choice depends on the purpose of the study. Data type of the studies also varies such that some studies employ national level data; however, regional level data is also utilized. Based on the availability of the data and methods for the analysis, the use of the micro level data at household or firm level is also increasing. While analyzing the survey of Taylor (1975), we have touched upon the previous discussions on the aggregation level from different views. Data type determines the method to be employed; basically, we can divide the methods into time series methods and panel data methods. All these factors besides, the time period and country analyzed, lead the studies to have different conclusions and elasticity estimates. As there are wide variations in the elasticity estimates, we cannot obtain consensus estimates for elasticities and also general conclusion. Below, we review the some interesting recent studies after summarizing the findings of the papers analyzing electricity demand of Turkey.

3.2. Aggregate Electricity Demand Studies for Turkey

In this section, we review the aggregate electricity demand studies for Turkey. In Table 3.1, details for each study are given. The earliest works on electricity demand analysis for Turkey, up to our knowledge, were by TEK (1975), Soysal (1986) and Şahin (1986). TEK (1975) regressed electricity consumption on its one-year lag, GNP, urbanization ratio, and population having access to electricity (Akan and Atak, 2003: 25).

Soysal (1986) estimated energy and electricity demand models by using OLS in the context of multiple regression analysis for Turkey and a group of countries. Electricity consumption was explained as a function of GNP at constant prices, corrected electricity price, and time. She found that electricity demand is highly income elastic, but price inelastic.

Bakırtaş et al. (2000) have analyzed the long run relation between electricity demand and income for Turkey using annual data including the period from 1962 to 1996 using cointegration technique and performed forecasting for years between 1997 and 2010 utilizing univariate ARMA process. To test the cointegration among the variables, Engle-Granger two-step procedure and Johansen's Cointegration procedure were applied. The results of both procedures showed that per capita electricity consumption and per capita real income are cointegrated which means that there is long run relationship between the variables. From the estimation of error correction model, short run and long run income elasticities were obtained as 0.692 and 3.134, respectively; higher than the ones for other countries indicating that income plays an important role in the electricity consumption. As there is problem of heteroscedasticity which is believed to be due to the year 1975, a dummy variable which captures the delayed effects of the oil price shock at the end of 1973 and Cyprus war in 1974 was added to the ECM.

Other study by Akan and Tak (2003) examined the electricity demand for aggregate, industrial, commercial, residential, official buildings, and general enlightenment sectors. In general, in the electricity demand model, they have included income and price specific to each sector as explanatory variables; however, price variables were excluded for official buildings and general enlightenment. The findings showed that demand is much more responsive to income changes compared to price. The estimated ECMs were employed for forecasting purposes for the period between the years 2001 and 2005 under three different scenarios on the income growth.

Erdoğdu (2007) estimated and forecasted the total electricity demand for Turkey by employing partial adjustment model, and performing cointegration analysis and Autoregressive Integrated Moving Average modeling using quarterly time series data on real electricity prices, real GDP per capita and net electricity consumption per capita over the period from 1984 to 2004. Estimation results of the partial adjustment model showed that there is little difference between the long run and the short run elasticities which is expected as the speed of adjustment to the long run equilibrium is higher; however, long run demand is relatively more elastic than short run demand. And also, as mentioned by Erdoğdu (2007), both estimated income elasticity and price elasticity are quite low implying that the firms with monopoly power or the firms in oligopolistic market structure may abuse their power to obtain monopoly rent as consumers do not respond much to increases in price; besides, level of income affect the demand more than price and demand is more responsive to income changes in the long run. Augmented Dickey Fuller tests indicated that the logarithms of the variables are I(1). Thus, in order to determine the relation defined by PAM is not spurious, cointegration analysis was performed by applying Augmented Engle-Granger test and Cointegrating Regression Durbin-Watson test. Based on the results of these two tests, it was shown that there is cointegration among the variables, so the PAM in the study was the appropriate model for electricity demand estimation. Forecasting of electricity demand was performed by using annual data covering the period from 1923 to 2004 based on ARIMA modeling. Forecast results exhibited that there is an electricity demand growth in Turkey. The forecasts obtained from the

ARIMA model and official forecasts provided from TEIAŞ based on two scenarios were compared after some manipulations made to official forecasts. Comparison showed that there is important difference between two forecasts.

For Turkey, another study was performed by Maden and Baykul (2012). They have employed Johansen maximum likelihood based cointegration test in order to test the existence of long run relation between per capita electricity consumption, per capita GDP, and electricity price. The result of the test indicated the presence of unique cointegration vector among the variables. In the long run, they have found that electricity demand is inelastic with respect to income, whereas, elastic with respect to electricity price and all the coefficients are significant. The estimation results of error correction model showed that in the short run, the same conclusion applies, however, consistent with the a priori expectations, long run elasticity estimates were found to be larger than the short run ones. In Section 3.3, we review the studies performed for other countries.

3.3. Aggregate Electricity Demand Studies for other Countries

For other countries also, as stated by Madlener (1996) and Dahl (2011), electricity demand is highly studied compared to any other energy product because of the availability and high quality of the data. Below, we summarize the some interesting studies on total electricity demand mostly related to the estimation of price and income elasticities classified according to the data type as panel data, time series data, and cross section data.

3.3.1. Panel Data Studies

In this section we summarize the methods and findings of the previous studies employing panel data. Hsiao et al. (1989) have analyzed regional peak demand and electricity demand in Ontario, Canada, including nine municipal regions using monthly data over sixteen years from January 1967 to December 1982 based on

Dynamic Partial Adjustment Specification. The factors affecting the electricity demand were taken as economic factors, climatic factors, and regional seasonal specific factors. Among them, the economic factors included income, price of electricity and price of substitutes which were all in real terms. Price of substitutes was proxied by real price of natural gas. The price of electricity was represented by end use sectors' demand charge and energy charge. On the other hand, 12 regional dummy variables were added to reflect regional seasonal specific factors. To account for climatic factors, cooling degree days and heating degree days were used. Other economic-social and weather factors were ignored as there may be some possible collinearity problems. The results of four different models, that use different assumptions related to the coefficients across and within regions, were compared with each other. Load impact factors were calculated, accordingly. In the first model, coefficients were assumed to be fixed and vary across regions. Therefore, the model for each region was estimated separately. The second model assumed that all the coefficients were same for all regions; in this model geographic differences were not considered. The third model based on Swamy type random coefficient model, took the coefficients to be randomly distributed with common mean and variance-covariance matrix. The last model using mixed fixed and random coefficients approach, assumed that coefficients of regional-seasonal specific factors were fixed and differed across regions and coefficients of economic and weather factors were randomly distributed. One period ahead prediction was performed to see the performance of different models. Results of estimation and prediction showed that one should consider the heterogeneity across regions and among four models, the mixed fixed and random coefficient model yields best results.

Diabi (1998) investigated the determinants of total electricity demand. Apart from electricity price and income variables, he considered other factors such as urbanization, price of electrical appliances and temperature. Based on a partial adjustment model, he found that electricity demand is inelastic with respect to income and own-price and also results showed high adjustments to the long run equilibrium. Another important finding noticed is that the significant and larger influence of urbanization variable on electricity demand relative to real income.

Based on the regional data, another study was performed by Atakhanova and Howie (2007). They have estimated the aggregate electricity demand for Kazakhstan using the panel data on 14 oblasts and city of Almaty covering the period from 1994 to 2003. In the analysis, they have assumed that supply of electricity is perfectly elastic as in the studies of Green (1987) and Bohi (1981) and also because of high transfer costs, they have agreed to ignore the shifts in fuel types due to a short run increase in relative price of electricity. In all models in the study, growth rate specification was utilized. For the aggregate electricity consumption, Gross regional product, retail electricity prices, population, industrial share in the total gross regional product and efficiency in the industrial sector were considered as driving variables and the income elasticity change possibility after 1999 was captured by including interaction dummy with the gross regional product. The model was estimated under methods of fixed effects, random effects and FGLS. Estimation and specification test results showed that the random effects model was preferred. The estimation results indicated that the signs of the all the coefficients of the variables are in line with a priori expectations; however some of the coefficients are insignificant. The main driving factors of the aggregate electricity consumption were found to be GRP, industrial share of GRP, industrial efficiency and they have found that income elasticity of aggregate electricity demand significantly varies after 1999. In the study, the demand model was also used for forecasting purposes. Forecasts were performed for years 2010 and 2015 under medium, high and low economic growth scenarios and under different assumptions on population growth rate considering different levels of policy intervention. The main conclusion of the study is that only under active policy intervention which includes 2 % annual growth in the real electricity prices, 1.5 % annual service sector efficiency growth and 6 % annual service sector efficiency growth, the future demand can be met by the planned capacity expansion in the supply side.

Chaudhry (2010) analyzed the total electricity demand in a panel data analysis framework. He determined the relationship between income and electricity demand for a group of 63 countries over a 11- year period from 1998 to 2008. In the cross-country analysis, fixed effects model in which electricity consumption per capita explained by real GDP per capita and average electricity prices was estimated. Estimation result indicated that %10 increase in income per capita is associated with %6.9 increase in electricity consumption per capita. Estimation of the same model for a subsample of low and middle income countries, gives income elasticity coefficient similar to that of the entire sample.

Lee and Lee (2010) have explored the electricity demand relation for OECD countries using panel unit root tests, panel cointegration tests, panel cointegration model, and panel causality tests. Per capita electricity consumption was modeled as a function of per capita real income and real electricity prices. They have applied first generation panel unit root tests, panel cointegration tests of Pedroni (2004) and Kao (1999), and Johansen Fisher-type panel cointegration test. Tests indicated the evidence of cointegration among the variables. Long run relation was estimated by FMOLS and results showed that long run electricity demand is income-elastic and price-inelastic. In the long run, significant positive effect of income and insignificant negative effect of price were found. In order to determine the direction of causality among the variables, panel Granger causality tests were performed in the framework of panel VECM assuming homogeneous short run dynamics across the countries. Panel VECM was estimated by GMM method proposed by Arrellano and Bond (1991). They have found that strong bidirectional causality exists between electricity consumption and income, however, there is uni-directional causality from income and price to electricity consumption in the long run and the short run. Price was found to be exogenous in the long run and the short run. Therefore, they have recommended the implementation of electricity efficiency and conservation policies in order to challenge with the concerns about economic growth and environmental sustainability. In the next section, we analyze some of the time series data studies.

3.3.2. Time Series Data Studies

In this section we summarize the methods and findings of the previous studies employing time series data. Nasr et al. (2000) have estimated electricity consumption models for Lebanon for the different periods over the years from 1993 to 1997 using monthly data. Sub-periods were determined according to the rationing level. Different model specifications were employed to explain electricity consumption as a function of total imports and degree days. For the period 1993-1994 in which extensive rationing was implemented and thus the electricity demand was supply-driven, unsatisfactory results were obtained from the estimations. For the other two periods 1995-1997 and 1996-1997, positive and significant effects of total imports and degree days were obtained both in the long run and the short run. In addition, Johansen(1988) and Engle and Yoo (1987) cointegration tests indicated the evidence of significant long run relation among the electricity consumption and explanatory variables.

For the Gulf Cooperation Council countries (GCC), Al-Faris (2002) performed an electricity demand analysis. Electricity consumption was modeled as a function of own price, economic activity measure (GDP), and price of LPG. From the estimation results for each six country, he found that in the short run, electricity demand is inelastic with respect to income and own price, however, in the long run elasticities are larger implying that policies are much more effective in the long run; in addition he mentioned that the relatively small cross price elasticity indicate the imperfect substitution of LPG.

The various methods for the estimation of long run and short run electricity demand models were compared by Fatai et al. (2003). They have modeled aggregate electricity demand by considering the following explanatory variables: real GDP, electricity price index for total final electricity consumption, and price of substitutes for electricity proxied by CPI. Based on Johansen multivariate cointegration test and Pesaran (1996, 1998) bounds testing approach, the evidence of only one cointegration relation between total final electricity consumption and real GDP, electricity price index for total final electricity consumption, and CPI was established. The cointegration relation and the corresponding error correction model were estimated by Engle-Granger OLS method, FMOLS, and Pesaran et al. (1996, 1998) ARDL approach. They have found that long run and short run aggregate electricity demand is price-inelastic, and short run aggregate electricity demand is income-inelastic irrespective of the method employed. However, the estimation results from different methods except ARDL approach showed that aggregate electricity demand is elastic with respect to income in the long run. CUSUMSQ stability test indicated the stability of coefficient estimates from all the methods. The comparison of the forecasting performance of the methods showed that forecasts from ARDL approach outperforms the others based on different forecasting performance measures.

Lin (2003) estimated aggregate electricity consumption model in order to forecast the future electricity demand and thus, to determine the investment requirements and measure the environmental impacts. Cointegration model was estimated for different two periods, namely whole period and post-reform period, respectively. In the model, electricity consumption was assumed to be determined by the following variables: population, income, fossil fuel price index as a proxy for electricity price, variable controlling for structural change resulted from the decline in the proportion of heavy industry, and energy intensity index to reflect the energy efficiency improvement. The results showed that after the economic reforms, electricity demand becomes more responsive to the changes in the variables and therefore, more significant coefficients were obtained. All the factors contributed significantly to electricity demand growth. Besides, in order to determine the short run response of electricity demand to the same factors, error correction model was estimated based on the cointegration relations obtained. Lin (2003) found that again all the factors have significant contributions in the short run, however, short run fluctuations in the electricity demand does not seem to have significant effects on long run relation.

Kamerschen and Porter (2004) have compared the flow adjustment model (PAM) with the simultaneous equations model (SEM). They have observed that the estimation results of SEM are in line with the theoretical expectations, however, the coefficients on some of the variables in the PAM have signs contrary to the theory; therefore, they preferred SEM because the ignorance of price endogeneity could have caused bias in the estimates obtained from the estimation of PAM. Following Halvorsen (1975), simultaneous supply and demand model was estimated for aggregate electricity consumption. Simultaneous equations model is consisted of two equations, one for average annual electricity sales per customer, and the other for real marginal electricity price. In the former equation, real marginal electricity price, real annual GDP, real natural gas price, and weather variables were included as explanatory variables. The marginal electricity price was explained by average annual electricity sales per customer, costs of labor, composite fuel, and capital in the second equation. Three versions of the model were estimated based on the weather variables included into the model such as, the version with heating degree days only, with only cooling degree days, and with both variables. From the estimation of the models, they have found that the least price sensitive is the total electricity consumption compared to other sectors.

De Vita et al. (2006) have analyzed long run total electricity demand relation. As explanatory variables, total GDP, marginal electricity price, air temperature, HIV incidence rate, marginal price of alternative energy forms, namely diesel and kerosene, and a dummy variable reflecting the independence after March 1990 were employed. They have performed bounds testing to test the cointegrating equation. Test results showed the evidence of long run relation among the variables. In the long run, they have found that weighted national marginal electricity price, total GDP, and mean minimum temperature significantly affect the total electricity demand and there is not any significant substitution possibilities among electricity and other energy forms.

Amarawickrama and Hunt (2008) have compared different methods in order to test the cointegration between electricity consumption per capita, real income per capita, underlying energy demand trend, and average real electricity price; and estimate a cointegrating relation and ECM for the electricity consumption. Engle-Granger methods, FMOLS technique, ARDL bounds testing method, ARDL model, Johansen multivariate approach, and the structural time series model were employed. They have obtained similar estimates for short run elasticities; however, significant differences among the estimates of long run elasticities were observed. Another interesting finding of the study is that the short run elasticities are higher than the long run ones. They have explained this situation as a result of inflexible energy-using capital and appliance stock owned by households and firms or due to the wrong modeling of energy efficiency impact.

Abosedra et al. (2009) have compared the forecasting performance of various models, namely, reduced form static model, ARIMA, and exponential smoothing models. In the reduced form static model, real imports as a proxy for GDP, relative humidity, and degree days were taken as explanatory variables. All the factors positively and significantly affected the electricity demand, however, they did not provide the income elasticity of electricity consumption. They found that the forecasts obtained from ARIMA model outperformed the forecasts from other models.

Amusa et al. (2009) have investigated the determinants of total electricity demand in South Africa. They have included own average price of electricity and income (total GDP) into their model as explanatory variables. Based on ARDL bounds testing approach, existence of cointegration relation between electricity consumption and explanatory variables was shown. In the long run, only income has a significant and positive impact on electricity consumption. Long run elasticity of electricity demand with respect to income is larger than one indicating that electricity demand is highly responsive to the changes in income in the long run. Short run effect of income is only significant at 10% significance level. Significant and negative error correction term suggests a convergence to the equilibrium but slowly. Using the CUSUM statistic, they have showed that estimated ARDL model exhibits a stable electricity demand relation.

Bhargava et al. (2009) have performed electricity demand analysis at aggregate level. Based on an autoregressive model, aggregate electricity demand was related to its one lag, aggregate net state domestic product, average price of electricity, maximum electricity demand, weather variables, such as seasonal rain fall, temperature variability, and humidity variability. The analysis was also performed to a subperiod between 1980 and 1998 called pre-reform period. Aggregate electricity demand was found to be inelastic with respect to income and price in the short run, whereas in the long run, it is price inelastic and income elastic. They have obtained similar results for the pre-reform period. For the aggregate electricity demand, only electricity price, maximum demand, lagged demand, and seasonal rainfall have significant impacts. They have proposed some demand side management measurements along with supply side measures based on the previous studies and implementations in other countries focusing basically on energy efficiency improvement in all sectors, time-of-use pricing, rationalizing the tariff structure of agricultural sector, consumer awareness campaigns and trainings in order to decrease energy waste, introducing interruptible tariff structure, use of renewable energy sources, generating capacity expansion, interregional electricity exchanges, and encouragement of efficient autoproduction. Lastly, they have taken attention to the urgent need for comprehensive energy policy because of the price-inelastic nature of electricity demand.

Issa and Bataineh (2009) have examined aggregate electricity demand in Jordan by a model which explained total electricity consumption as a function of real GDP per capita, real price of electricity, and energy efficiency in industrial sector. Results showed that there is evidence of significant positive relation with GDP and negative and significant effects of electricity price and energy efficiency.

Aggregate electricity demand for Pakistan was analyzed by Khan and Qayyum (2009). In the model of aggregate electricity demand, real income, real electricity price, number of customers, and temperature were employed as explanatory variables. They have followed Pesaran et al. (2001) approach to test for cointegration. Bounds test for aggregate electricity demand relation showed the evidence of cointegration. Using CUSUM and CUSUMSQ tests, stability of the relations were established. The results suggested that temperature has positive and significant influence in the long run and the short run. Other important finding was such that short run aggregate electricity consumption is elastic with respect to income. However, in the long run, aggregate demand is income elastic implying electricity is a luxury. Short run price elasticities are significant, however, electricity demand is price-inelastic in the short run. Long run price elasticity is significant and higher than one. They have found that long run elasticities are larger than short run's. And, lastly, number of customers significantly and positively affects the long run and short run electricity demands.

An econometric analysis of aggregate electricity demand was performed by Inglesi (2010) based on cointegration and error correction models in order to evaluate the impact of proposed price increase. In the long run, electricity demand was explained by real disposable income and average real electricity price. In the short run, using error correction model, the determinants of electricity demand were taken as population and real GDP. Based on Engle-Granger cointegration test, Inglesi (2010) established the existence of cointegrating relation among the variables. In the short run and the long run, all the variables have significant and theoretically expected effects on electricity demand. Long run electricity demand was found to be inelastic with respect to income and own-price. Inglesi (2010) also found that 10% positive shock to the income and price in the long run cause electricity demand to increase and decrease, respectively. Based on two scenarios about future economic growth, electricity demand was forecasted for the period between 2006 and 2030 assuming 1% increase in the population annually, a 100% increase in the electricity price over first four years and then during last 15 years period fixed electricity price. The results showed that electricity demand declines as price increases and begins to increase at low growth rate after the stabilization of price at a constant value.

Jamil and Ahmad (2010) have investigated the effects of electricity price and real GDP on electricity demand at aggregate level by using cointegration analysis. Johansen's cointegration test revealed the existence of cointegration among the variables. Long run electricity demand was found to be income elastic and inelastic with respect to price. In addition, they have performed Granger Causality test in the context of VECM model. Tests on the joint significance of short run and long run effects indicated the unidirectional causality from GDP to electricity consumption. Besides, at the aggregate level, the results of joint tests showed the one-way causality from electricity price to electricity consumption. Weak exogeneity of income/output and price variables were also validated by variance decomposition analysis. As a policy implication of the results, they have suggested the policies on electricity conservation and efficiency, and on the supply side, they have emphasized on the planning and investment on capacity additions for both generation and transmission, and the policies for stimulating competition and private sector involvement.

Sohaili (2010) measured the impact of removing electricity subsidies on air pollution in Iran in the context of error correction version of ARDL model in which real price of electricity and real GDP were employed as determinants of electricity demand. Results of bounds testing approach showed the existence of long run electricity demand relation. From the estimation of the ARDL model, they have found that in the long run and short run, real price of electricity and real GDP have significant effects on electricity demand with correct signs. Findings showed that electricity demand is inelastic with respect to income and own-price, however, effects of price and income changes will be more pronounced in the long run as expected. Therefore, Sohaili (2010) claimed that 400% increase in electricity price due to cut in subsidies will lead to a decline of 12% and 56% in the short run and the long run electricity demand, thus in the environmental pollution.

Alter and Syed (2011) have explored the determinants of aggregate electricity demand using cointegration and error correction model which explained the aggregate and sectoral electricity consumption considering the following explanatory variables: aggregate real income, aggregate weighted price, stock of electric appliances, and aggregate number of customers. Johansen cointegration test indicated the presence of long run relation among the variables. In order to examine the short run dynamics, error correction model was estimated by the same set of variables and results showed a stable long run relation. Both in the short run and the long run, coefficients on income and price are significant. They have found that in the long run, electricity demand is a necessity. Findings suggested that long run aggregate electricity demand is price inelastic. On the other hand, in the short run, electricity is necessity and also, electricity demand is inelastic with respect to price. Stock of electrical appliances and number of customers were found to be significant determinants of long run and short run aggregate electricity demand.

Based on cointegration analysis and error correction model, Bekhet and Othman (2011) have analyzed the long run and short run aggregate electricity demand for Malaysia. They have employed electricity tariff, real GDP, gas price, urban population and rural population as explanatory variables in their electricity consumption model. After finding the presence of cointegration for the electricity demand relation, they have estimated the long run relation, then error correction model. Results indicated that in the long run, electricity is a necessity as they have obtained significant, positive, and inelastic income elasticity, and the long run electricity demand is highly and significantly responsive to the changes in urban population with a positive correlation. However, the effects of all the other variables were found to be insignificant. Also, in the short run, they have found that no variable have significant impact on electricity demand. In summary, short run and long run aggregate electricity demand is inelastic with respect to income and own-price. They have put forward that although tariff increase will not be so much effective to decrease the electricity consumption, this policy can help the government to increase its revenue. Also, they have further remarked the conflict between the country's development and government revenue gains by implementing such energy policy.

Ekpo et al. (2011) have studied the determinants of aggregate electricity demand based on ARDL approach proposed by Pesaran et al. (2001). Per capita electricity consumption was modeled as a function of per capita real GDP, electricity prices, total population, and industrial output. Bounds testing indicated the existence of the long run electricity demand relation. Estimation results obtained from the error correction model showed that in the long run, population, per capita income, and industrial output significantly and positively affect the per capita aggregate electricity consumption. The insignificance of coefficient on electricity price in the long run and the short run was explained by the price regulation of the government. In the short run, significant and positive contributions of population and per capita income were found; however, as mentioned by them, significant and negative impact of industrial output in the short run reflects the autoproduction of the firms as a result of unreliable electricity supply. CUSUM and CUSUMSQ tests indicated the stability of long run electricity demand model. Overall, electricity demand was found to be inelastic with respect to both income and price in the long run and the short run indicating that electricity is a necessity. From the findings, Ekpo et al. (2011) have drawn some policy recommendations such as liberalizing and reforming the electricity sector to eliminate the inefficiencies and ensure the supply reliability; and energy efficiency and conservation policies targeting at especially the residential sector.

The price elasticity of South Australian electricity demand was analyzed by Fan and Hyndman (2011). In their study, in addition to the price elasticity estimation for average annual demand, they have performed analysis of hourly price elasticity at different time periods, demand levels, and seasons, and, as well as, examination of price elasticity variations across year and seasons at different demand quantiles. However, here, we focused only on the analysis for average annual demand as the other analyses are out of scope of this literature review. In the model for average annual demand, they have utilized the following explanatory variables: annual population, gross state product, one period lagged average electricity price, cooling degree days, and heating degree days. Due to high collinearity between population and gross state product, from the regression, population variable was dropped. Positive effects of gross state product, cooling degree days, and heating degree days and negative impact of one period lagged average electricity price were found. The findings also showed that electricity consumption is inelastic with respect to own-price.

Jamil and Ahmad (2011) have considered aggregate real GDP, aggregate real electricity price, real diesel price, aggregate capital stock, and temperature represented by the sum of heating and cooling degree days as the determinants of aggregate electricity consumption. As in their previous study, they have applied Johansen's cointegration test in order to test for the existence of long run relation among the electricity consumption, economic activity, and electricity price in a multivariate context. The results of the test showed the existence of one cointegrating relation among the variables under the investigation. The estimation results of cointegrating equations indicated significant positive income and negative price elasticities in the long run which are all greater than one. And also, they have observed that in the long run, income elasticities are higher than price elasticities consistent with the findings of previous studies. Based on the estimation results of VECM model, in the short run, aggregate electricity demand was found to be price and income inelastic as the estimates of price and income elasticities are all smaller than one implying the lesser impact of short run conditions and besides, all are insignificant. When they have analyzed the effects of the other variables in the short run, they have found that the capital stock affects positively and significantly electricity demands. As a result, they have revealed that their results are consistent with the previous studies on the developing countries obtained higher income elasticity estimates and also higher long run elasticities compared to short run. Further, they have claimed that electricity price can be used as an effective policy tool for energy efficiency and conservation. According to them, diversification of resources in electricity generation, generation capacity expansion, investments in transmission and distribution networks, efficiency improvement are essential to ensure sustainable electricity supply.

Madlener et al. (2011) have investigated the interfuel substitutions between electricity, oil, and natural gas at aggregate level. Cost shares obtained from translog cost function were estimated using SUR method. They have argued that it is difficult to draw a general conclusion as they have obtained wide range of estimates for cross- and own-price elasticities for each sector, country, and fuel.

Yépez-García et al. (2011) have provided a short review of some recent empirical studies of electricity demand focusing on the studies performed for Latin American and Caribbean region. As mentioned in other reviews, they have observed wide variation in the estimates for price and income elasticity of electricity demand and noticed the importance of distinguishing between short run and long run for the analysis of electricity demand and also the discussion on the relevance of average or marginal price for the electricity demand, especially in the cases of the multi-step block pricing structure. In order to perform scenario analysis to year 2030, they have estimated electricity demand elasticities with respect to income and price for each 17 countries using a model which relates aggregate total electricity consumption to GDP and electricity price measured by the weighted average electricity tariff for each country. As theoretically expected, they have found significant positive income elasticity estimates for all countries and except for Chile, Colombia, Nicaragua, and Venezuela, RB, significant negative price elasticity estimates. Estimation results indicated that electricity consumption is income elastic for all countries except Paraguay and Venezuela, RB; and price inelastic with exceptions of countries as, Ecuador, Honduras, Paraguay, and Uruguay.

Gam and Rejeb (2012) have investigated the effectiveness of price and non-price policies in order to control the electricity consumption. Based on KLEM model, they have estimated own- and cross-price elasticities of factor demands and also partial substitution elasticities by Zellner's iterative procedure and reached a conclusion that policies on electricity price and energy efficiency improvements of the capital stock together will help to control the electricity consumption as the results of the estimations indicated the responsiveness of electricity demand to its own price and the complementarity between electricity demand and capital stock, thus the responsiveness of electricity demand to the prices of capital stock. They have also showed that there is a positive relation between electricity consumption and GDP which is aggregated in the labor variable.

Zaman et al. (2012) have analyzed the determinants of electricity demand in Pakistan. Model included foreign direct investment, GDP per capita, population growth as explanatory variables for the electricity consumption per capita. By following Bounds testing approach, they have showed the existence of cointegration among the variables. Short run and long run elasticities with respect to each factor were obtained from the estimation of an ARDL model. The findings revealed the significant and positive impacts of all the explanatory variables on the long run and the short run electricity demand, however, major determinant of electricity demand was found to be population growth. Stability of the estimated parameters was shown by the use of CUSUM and CUSUMSQ tests. They have also performed short run Granger causality test and found the existence of unidirectional causality from population growth to electricity demand, and from population growth and foreign direct investment to GDP per capita.

Ziramba and Kavezeri (2012) have modeled aggregate electricity consumption as a function of real GDP and real electricity tariff. By employing Bounds testing approach, they have showed the presence of stable long run electricity demand relation. In the long run, income has positive and significant effect; while, impact of electricity price was found to be insignificant with a negative sign. Cointegration analysis of aggregate electricity demand performed by Ziramba and Kavezeri (2012) showed that in the long run, aggregate electricity demand is income elastic and price inelastic for Namibia. They have illustrated that pricing policy alone is not fully effective to reduce the aggregate electricity consumption. In section 3.3.3, we focus on the aggregate electricity demand studies based on cross-section data.

3.3.3. Cross-Section Data Studies

In this section we summarize the methods and findings of the previous studies employing cross section data. Contreras (2008) analyzed the regional U.S. electricity demand. He examined 9 regions for the year 2002. Electricity demand model was estimated using the cross-sectional data on 51 states and year 2002 considering regional specific factors by OLS. Double log specification was used. Electricity demand models were specified as a function of weighted average price for the total demand, state personal income, population, natural gas price, HDD and CDD, and regional dummies. Electricity demand per capita was also estimated. The results showed that natural gas price has positive but statistically insignificant effect on electricity demand and there are significant regional differences. Coefficient on price variable has expected negative sign and it is significant. On the other hand, income variable positively and significantly affect total demand. For the total electricity demand, CDD variable has a significant and positive impact.

Up to here, we present the findings of previous studies, and models and methods employed. As mentioned earlier, it is very challenging to reach a general conclusion, as there is wide variation across the elasticity estimates because of the time period and country studied such that the countries are at different development stages. Eller (2010) claimed that there is a negative relation between economic development and energy consumption. Based on this claim, we can expect different responses to price and income changes across time and country.

In the light of these studies, we build our model. We discuss modeling issues in the next section.

Table 3.1 Econometric Total Electricity Demand Studies

Author	Data	Country/ Region	Method/ Model	Income Elasticities Short -run	Income Elasticities Long -run	Own Price Elasticities Short-run	Own Price Elasticities Long-run
Murray et al. (1978)	1958:01-1973:12 9 Virginia districts Pooled CS-TS	U.S.	Truncated estimation method	0.52	0.79	-0.62 to -0.39	-0.89 to -0.47
Reister (1986)	1960-1982 TS	U.S.	CES model Backcasting				--0.99
Soysal (1986)	1981 38 countries CS	38 countries	Multiple linear regression OLS		0.849		
Soysal (1986)	1963-1981 TS	Turkey	Multiple linear regression OLS	1.839		-0.0683	
Pouris (1987)	1950-1983 TS	South Africa	Unconstrained Distributed Lag Model OLS		0.26		-0.9
Hsiao et al. (1989)	1967:01-1982:12 9 municipal regions Panel CS-TS	Canada/ Ontario	Mixed Fixed and Random Coefficients Model	0.325	1.316	-0.006	-0.024
Whittaker and Barr (1989)	1963-1986 TS	South Africa	OLS		0.163		-1.02
Ramcharran (1990)	1970-1986 TS	Jamaica	-	1.65			
Bates and Moore (1992)	World bank data	Brazil	-			-0.2	-0.83
Balabanoff (1994)	1970-1990	Argentina	-		1.00		
Balabanoff (1994)	1970-1990	Brazil	-		1.73		-0.43
Balabanoff (1994)	1970-1990	Chile	-		1.65		
Balabanoff (1994)	1970-1990	Equador	-		1.95		
Balabanoff (1994)	1970-1990	Peru	-		0.70		
Diabi (1998)	1980-1992 5 Regions Panel CS-TS	Saudi Arabia	PAM Within estimation	0.171 to 0.326	0.203 to 0.487	-0.003 to -0.12	-0.004 to -0.14

Table 3.1 (Continued)

Author	**Data**	**Country/ Region**	**Method/ Model**	**Income Elasticities**		**Own Price Elasticities**	
				Short -run	**Long-run**	**Short-run**	**Long-run**
Bakırtaş et al. (2000)	1962-1999 TS	Turkey	Linear ECM	0.667	3.134		
Nasr et al. (2000)	1993:01-1997:12 TS	Lebanon	Static reduced form model, PAM, ECM	NA	NA	NA	NA
Lundmark (2001)	1980-1996	Namibia	-	-	-	-0.51	-0.863
Al-Faris (2002)	1970-1997 TS	Saudi Arabia	Cointegration model ECM	0.05	1.65	-0.04	-1.24
Al-Faris (2002)	1970-1997 TS	United Arab Emirates	Cointegration model ECM	0.02	2.52	-0.09	-2.43
Al-Faris (2002)	1970-1997 TS	Kuwait	Cointegration model ECM	0.70	0.33	-0.08	-1.10
Al-Faris (2002)	1970-1997 TS	Oman	Cointegration model ECM	0.02	0.79	-0.07	-0.82
Al-Faris (2002)	1970-1997 TS	Bahrain	Cointegration model ECM	0.02	5.39	-0.06	-3.39
Al-Faris (2002)	1970-1997 TS	Qatar	Cointegration model ECM	0.08	2.65	-0.18	-1.09
Akan and Tak (2003)	1970-2000 TS	Turkey	ECM	0.630	1.8098	-	-0.2212
Fatai et al. (2003)	1960-1999 TS	New Zealand	ECM Engle-Granger two step procedure FMOLS ARDL approach	0.24 to 0.46	0.81 to 1.24	-0.18 to -0.24	-0.44 to -0.59
Lin (2003)	1952-2001 TS	China	Johansen cointegration test Cointegration model MLH		0.856		-0.037
Lin (2003)	1978-2001 TS	China	Johansen cointegration test Cointegration model MLH		0.780		-0.016

Table 3.1 (Continued)

Author	**Data**	**Country/ Region**	**Method/ Model**	**Income Elasticities**		**Own Price Elasticities**	
				Short -run	**Long -run**	**Short -run**	**Long-run**
Kamerschen and Porter (2004)	1973-1998 TS	U.S.	Simultaneous equation approach, 3SLS	0.892 to 0.898		-0.14 to -0.15	
De Vita et al. (2006)	1980Q1-2002Q4 TS	Namibia	ARDL Bounds Testing for cointegration		0.589		-0.29
Atakhanova and Howie (2007)	1994-2003 14 oblasts and city of Almaty Panel TS-CS	Kazakhstan	Fixed effects, random effects, Panel FGLS	0.37 to 0.72			
Erdoğdu (2007)	1984:Q1-2004:Q4 TS	Turkey	PAM	0.057	0.414	-0.04	-0.29
Amarawickra-ma and Hunt (2008)	1970-2003 TS	Sri Lanka	Static and Dynamic Engle Granger method; FMOLS; Bounds testing approach; Johansen's ML approach; Structural time series model; ECM	1.82 to 1.96	0.99 to 1.96	0	-0.06 to 0
Contreras (2008)	2002 51 States CS	U.S.	OLS	0.89 & 0.19		-0.73 & -0.73	
Ma et al. (2008)	1995-2004 7 regions Panel CS-TS	China	Two stage Translog cost function Iterative Zellner SUR technique			-0.68	
Abosedra et al. (2009)	1995:01-2005:12 TS	Lebanon	Static reduced form model OLS	N.A.			
Amusa et al. (2009)	1960-2007 TS	South Africa	ARDL Bounds Testing	0.218	1.673	0.038	0.298

Table 3.1 (Continued)

Author	Data	Country/ Region	Method/ Model	Income Elasticities		Own Price Elasticities	
				Short -run	Long -run	Short -run	Long-run
Bhargava et al. (2009)	1980-2005 TS	India (state of Punjab)	Dynamic reduced from model OLS	0.717	1.342	-0.08	-0.15
Issa and Bataineh (2009)	1979-2008 TS	Jordan	Multivariate regression model LS	0.29		-0.09	
Khan and Qayyum (2009)	1970-2006 TS	Pakistan	Bounds testing ARDL model	1.09	4.7	0.25	-1.64
Chaudhry (2010)	1998-2008 63 Countries Panel CS-TS	63 Countries	Fixed effects model	0.69		0.012	
Chaudhry (2010)	1998-2008 Low and Middle Income Countries Panel CS-TS	Low and Middle Income Countries	Fixed effects model	0.65		0.036	
Inglesi (2010)	1980-2005 TS	South Africa	Cointegration model ECM	0.820	0.415	-	-0.564
Jamil and Ahmad (2010)	1960-2008 TS	Pakistan	Johansen cointegration		1.70		-0.83
Lee and Lee (2010)	1978-2004 25 OECD countries Panel CS-TS	OECD	Panel cointegration model FMOLS		1.08		-0.01
Sohaili (2010)	1970-2008 TS	Iran	Bounds testing approach ARDL model	0.26	0.27	-0.03	-0.14
Alter and Syed (2011)	1970-2010 TS	Pakistan	Cointegration model ECM	0.315	0.251	-0.19	-0.853
Bekhet and Othman (2011)	1980-2009 TS	Malaysia	Cointegration ECM	0.25	0.84	-0.42	0.59
Ekpo et al. (2011)	1970-2008 TS	Nigeria	Bounds testing approach ARDL model	0.228	0.587	-0.23	-0.449

Table 3.1 (Continued)

Author	Data	Country/ Region	Method/ Model	Income Elasticities		Own Price Elasticities	
				Short -run	Long -run	Short-run	Long -run
Fan and Hyndman (2011)	1997-2008 TS	South Australia	Linear regression model OLS			-0.363 to -0.428 (Semilog model) -0.4165 (Double log model)	
Jamil and Ahmad (2011)	1961-2008 TS	Pakistan	Johansen cointegration VECM	0.32	1.56	-0.07	-1.27
Madlener et al. (2011)	1978-2006 TS	Germany, France, Italy, Spain, and the UK	Static Translog cost function Fuel share models SUR			-1.59 to 0.64	
Yépez-García et al. (2011)	1978-2007 17 countries TS	Latin American and Caribbean countries	Multivariate regression analysis OLS	0.48 to 2.24		-1.67 to 0.03	
Gam and Rejeb (2012)	1990-2007 TS	Tunisia	Translog production function Zellner's iterative procedure	1.10		-0.681	
Maden and Baykul (2012)	1970-2009 TS	Turkey	Cointegration model, ECM	0.168	0.928	-1.440	-6.85
Zaman et al. (2012)	1975-2010 TS	Pakistan	ARDL Bounds testing, ECM	0.343	0.973		
Ziramba and Kavezeri (2012)	1993Q1-2010Q1 TS	Namibia	ARDL Bounds testing, ECM	0.235	1.121	-	-0.32

Source: Barnes, Gillingham, and Hagemann (1981), Table 6; Bohi and Zimmerman (1984), Tables 1, 4, and 5; Dahl (1993), Tables 6, 8, and 10; Bose and Shukla (1999), Table 3; Khanna and Rao (2009); Bernstein and Madlener (2011), Table 1; Bernard, Bolduc, and Yameogo (2011), Table 4; Author's own elaboration.

Note: OLS: Ordinary Least Squares; LS: Least Squares; TSLS: Two-Stage Least Squares; 3SLS: Three Stage Least Squares; MLH: Maximum Likelihood; IV: Instrumental Variable; CCR: Canonical Cointegrating regression; TVC: Time varying coefficient; FC: Fixed coefficient; PAM: Partial Adjustment Model; ARDL: Autoregressive Distributed Lag; FGLS: Feasible Generalized Least Squares; ECM: Error Correction Model; VECM: Vector ECM; GM: Group Mean; FMOLS: Fully Modified OLS; DOLS: Dynamic OLS; PMGE: Pooled Mean Group Estimation, GMM-BB: Generalized Method of Moments –Blundell and Bond (1998); NLS: nonlinear least squares; FIML: Full Information MLH, TL: translog; GL: generalized Leontief; n.s. means not significant.

CHAPTER 4

MODEL

In this section, we build our empirical model based on the economic theory and the empirical literature. In the electricity demand models, as for any other good, income and price are suggested as the key determinants by Heshmati (2012), besides, based on the availability and aggregation level of the data, he noticed the incorporation of the following variables into the model specification: market and climate characteristics such as weather and seasonal factors, firm and industry characteristics, population and household composition, and non-price control variables like, restrictions, education, and campaign. However, while modeling electricity demand, we need to consider the distinguishing features of electricity from other goods. First, as electricity is not storable, demand must be met by sufficient supply at any time. Second, electricity demand is a derived demand because, electricity is not demanded all on its own as it provides services only through the use of appliances, machines, and equipments. Therefore, this section focuses on the modeling issues for aggregate demand in Section 4.1. In Section 4.2, based on the theoretical and empirical literature, we present the empirical aggregate electricity demand model incorporating economic volatility.

4.1. Modeling Aggregate Electricity Demand

In the empirical literature, some studies have analyzed the aggregate electricity demand without sectoral disaggregation. Pouris (1987) claimed that unbiased estimates for the total economy and more stable relationships can be obtained at the aggregate level. By taking into account this remark, we prefer to study at the aggregate level in order to obtain elasticity estimates for the entire economy.

Karimu and Brännlund (2012) have attempted to the theoretical derivation of the aggregate energy demand model. They have argued that aggregate energy demand is composed of the final energy demand of households and the energy demand of firms as an input in their production processes. In the framework of derived demand and by employing two stage process, they have derived the model by considering the consumer's utility maximization and firm's cost minimization (profit maximization) problems under the assumption of weakly separable preferences over energy and non-energy goods for households and separability of energy inputs from other non-energy inputs for the firms given the prices of goods and inputs. In their two stage process for the consumer's problem, the first stage includes the solution of the consumption decision between energy and non-energy goods, whereas, second stage deals with the problem of the non-energy consumption composition. Same argument was applied to the firm side. From the solution of each problem, they have expressed energy demand as a function of real income/output and real energy price and further, assumed that aggregate energy demand is determined by only real price of energy and real income per capita. By adding a third stage to the process in which the composition of energy consumption is determined, electricity demand function can be obtained.

Some of the empirical studies that analyzed the aggregate electricity demand include Murray et al. (1978), Reister (1986), Soysal (1986), Pouris (1987), Hsiao et al. (1989), Whittaker and Barr (1989), Ramcharran (1990), Bates and Moore (1992), Balabanoff (1994), Diabi (1998), Bakırtaş et al. (2000), Nasr et al. (2000), Lundmark (2001), Al-Faris (2002), Akan and Tak (2003), Fatai et al. (2003), Lin (2003), Kamerschen and Porter (2004), De Vita et al. (2006), Atakhanova and Howie (2007), Erdoğdu (2007), Amarawickrama and Hunt (2008), Contreras (2008), Ma et al. (2008), Abosedra et al. (2009), Amusa et al. (2009), Bhargava et al. (2009), Issa and Bataineh (2009), Khan and Qayyum (2009), Chaudhry (2010), Inglesi (2010), Jamil and Ahmad (2010), Lee and Lee (2010), Sohaili (2010), Alter and Syed (2011), Bekhet and Othman (2011), Ekpo et al. (2011), Fan and Hyndman (2011), Jamil and Ahmad (2011), Madlener et al. (2011), Yépez-García et al. (2011), Gam and

Rejeb (2012), Maden and Baykul (2012), Zaman et al. (2012), and Ziramba and Kavezeri (2012). Among them, Murray et al. (1978) have calculated price and income elasticities for entire economy as a weighted average of separate elasticities of each customer class, however, as mentioned above, this method was critized by Pouris (1987). On the other hand, Reister (1986) employed a CES model to estimate the elasticities for aggregate electricity demand, however, in her survey, Dahl (1993) did not provide the information on the variables of the model. Pouris (1987), Fatai et al. (2003), Amusa et al. (2009), Jamil and Ahmad (2010), Sohaili (2010), Yépez-García et al. (2011), and Ziramba and Kavezeri (2012) have only considered real marginal/average electricity price and real income as explanatory variables in the electricity demand model. The model proposed by Pouris (1987) was employed by Whittaker and Barr (1989), but in double log form. In addition to the real marginal/average electricity price and real income, in the literature, following determinants of aggregate electricity demand were considered: time trend by Soysal (1986); population by Erdoğdu (2007), Chaudhry (2010), Inglesi (2010), Lee and Lee (2010), and Maden and Baykul (2012); price of LPG by Al-Faris (2002); population and time trend by Akan and Tak (2003); population and underlying energy demand trend by Amarawickrama and Hunt (2008); industrial energy efficiency and population by Issa and Bataineh (2009); number of customers and temperature by Khan and Qayyum (2009); stock of electric appliances and aggregate number of customers by Alter and Syed (2011); population and industrial output by Ekpo et al. (2011); urbanization, price of electrical appliances, and temperature by Diabi (1998); population, variable controlling for structural change resulted from the decline in the proportion of heavy industry, and energy intensity index to reflect the energy efficiency improvement by Lin (2003); real natural gas price, heating and cooling degree days by Kamerschen and Porter (2004); population, industrial share in the total gross regional product, and efficiency in the industrial sector by Atakhanova and Howie (2007); gas price, urban population and rural population by Bekhet and Othman (2011); population, heating and cooling degree days by Fan and Hyndman (2011); real diesel price, degree days, and aggregate capital stock by Jamil and Ahmad (2011); real natural gas price as a price of substitute, cooling and heating degree days to measure climatic factors, and regional and seasonal specific factors by Hsiao et al. (1989); air temperature, HIV incidence rate, marginal price of diesel and kerosene by De Vita et al. (2006); population, price of natural gas, cooling and heating degree days, and regional specific factors by Contreras (2008); and lastly, maximum electricity demand, and weather variables, such as seasonal rain fall, temperature variability, and humidity variability by Bhargava et al. (2009). Only per capita income was employed by Bakırtaş et al. (2000) as a determinant of long run per capita electricity demand. Due to the unreliability of the gross domestic product data and rationing policy, Nasr et al. (2000) have specified electricity consumption as a function of total imports and degree days, however, for the same country, Lebanon, in addition to the former explanatory variables, Abosedra et al. (2009) have included relative humidity to the model. For Pakistan, Zaman et al. (2012) have modeled electricity consumption per capita by considering foreign direct investment, GDP per capita, population growth as explanatory variables. Some of the studies have employed fuel share models to obtain own- and cross-price elasticities such as Ma et al. (2008), Madlener et al. (2011), and Gam and Rejeb (2012). In the next section, we present our empirical model to be employed in the applications section.

4.2. Empirical Aggregate Electricity Demand Model with Economic Uncertainty

In the light of economic theory and literature, we build the following model in order to analyze the electricity demand in the context of panel data methods;

$$\begin{aligned} lnpcec_{it} &= \alpha + \beta * lnpcgdp_{it} + \gamma * lnrep_{it} + \theta * uratio_{it} \\ &\quad + \vartheta * hdd_{it} + \varphi * cdd_{it} + \lambda * h_t + \varepsilon_{it} \end{aligned} \tag{4.1}$$

where, i=1,...,N and t=1,...,T are subscripts for cross-sectional units and time periods; lnpcec, lnpcgdp, and lnrep are the natural logarithms of per capita electricity consumption, per capita gross domestic product, real electricity price; uratio, hdd, cdd, and h denote urbanization ratio, heating degree days, cooling degree days, and economic uncertainty, respectively. As we employ double-logarithmic functional form, the coefficients β and γ give income and own price elasticities invariant at any levels of an explanatory variable. Double-logarithmic form is the most preferred functional form and Chang and Hsing (1991) have attributed the common use of double-log form to the easy estimation and direct derivation of elasticities from the estimated coefficients. Double-logarithmic form is “chosen also for reducing the effect of extreme electricity consumption and income on parameter estimates” (Khanna and Rao, 2009: 579). Infact, by employing double-log form, we assume Cobb-Douglas type utility and cost/production functions. In order to avoid from the aggregation problem and although it is not so much realistic, we build our model based on the assumption that all the electricity consuming groups show identical consumption behavior. Following Green (1987), Bohi (1981) and Atakhanova and Howie (2007), we assume electricity supply is perfectly elastic and we do not allow for the interfuel substitution. Assumption on supply of electricity is necessary because as mentioned by Bohi and Zimmerman (1984), if supply is not perfectly elastic, then the relation between supply and price should be incorporated into the price-demand relation in order to avoid biased estimates. However, as in the most of the countries, consumers are subject to the regulated prices, the endogeneity problem for electricity price will not exist as mentioned by Green et al. (1986). Another assumption noticed by Bohi and Zimmerman (1984) is on the supply of electricity-using capital equipment which is assumed to be perfectly elastic. Because of high transfer costs, following Balestra and Nerlove (1966), Atakhanova and Howie (2007) have agreed to ignore the shifts in fuel types due to a short run increase in relative price of electricity in their analysis. Denton et al. (2003) have also formulated their model on the basis of this assumption. Diabi (1998) discarded the prices of substitute fuels from the aggregate electricity demand model as he argued that there are irrelevant due to the limited fuel substitution possibilities for the major end-uses of electricity. Another study in which the substitution possibilities are not allowed was by Filippini (1999). Filippini (1999) also excluded prices of substitute fuels from the residential electricity demand model a priorily because of the unavailability of some substitute fuels in some cities, and also, although they are available, he thought that it is unreasonable for the substitution of electricity by these fuels. Further prices of some other substitute fuels have very little variation across cities, also they were not included into the model by Filippini (1999). As observed by Bohi (1981), Bohi and Zimmerman (1984), and Khanna and Rao (2009), effects of the prices of substitute fuels were found to be insignificant, or small in the empirical studies under their investigation. This situation was explained as a result of the employment of partial equilibrium class of models by Bohi and Zimmerman (1984) and fuel technology constraint of the equipment by Khanna and Rao (2009) ignoring the dual-fuel technology of the equipment and autoproduction of electricity using other energy types. We reach the same conclusion when we analyze the estimation results of the aggregate electricity demand studies. Although Hsiao et al. (1989) and Al-Faris (2002) have found significant but small effect of substitute price implying imperfect substitution of electricity by natural gas and LPG, findings of other studies such as Kamerschen and Porter (2004), De Vita et al. (2006), Contreras (2008), Bekhet and Othman (2011), and Jamil and Ahmad (2011) show the absence of substitution of electricity by natural gas, gas, diesel, and kerosene. In addition to aforementioned studies, Pouris (1987) preferred to exclude the substitute fuel prices from the model and he explained the reasons why the previous studies have found insignificant cross-price effect. First, he attached this finding to the unique characteristics of electricity such as versatility, transferability, eligibility to fractional use and also he mentioned that it is the cleanest among all fuels for end use purposes. Second, Pouris (1987) put forward that electricity end users consider the relative costs of technologies using alternative fuels and availability of these technologies besides of relative fuel prices and this also restricts the substitution. Third, according to him, as many of these alternative fuels are utilized for the electricity generation, "the variations in their prices can be reflected at least partially in the price of electricity" (Pouris, 1987: 1272) and this can lead to the high correlation between the prices of electricity and alternative fuels, and thus the problem of collinearity when both prices are included. Therefore, based on Ockham's razor, we do not include price of substitute fuels into our model as they seem to be irrelevant.

A priori expectations about signs of coefficients are as follows: $\beta > 0, \gamma < 0, \theta > 0, \vartheta > 0, \varphi > 0, \lambda < 0$. Below, we give the reasonings for these expectations based on economic theory and results from the previous empirical studies.

We expect positive income elasticity as "similarly to other normal goods, the consumption of electricity is expected to increase with a rise in disposable income, the resulting increase in economic activity, purchases of electricity-using appliances" (Yépez-García et al., 2011: 161), and because "it is an indispensible input into the production function, increase in output necessiates a corresponding increase in electricity input and also capital formation, accumulation of electricity-driven machinery and durable equipment" (Al-Faris, 2002: 122); otherwise, negative income elasticity shows that electricity is an inferior good contrary to our expectation. If income elasticity is smaller than unity, then the electricity is a necessary good; however, income elasticity larger than unity implies that electricity is a luxury good.

Based on law of demand in the consumer theory, for ordinary and normal goods, expectation of negative relation between electricity demand and electricity price is plausible, whereas positive own-price elasticity is an indication that electricity is a Giffen good. Giffen good is an inferior good such that in Slutsky identity, the substitution effect is dominated by positive income effect producing a positive relation between own-price and demand. Producer theory suggests "downward sloping inverse factor demand curve by the assumption of diminishing marginal product" (Varian, 2003: 339), therefore, from the firm's side, also expectation of negative relation between electricity demand and its price is supported. As we consider electricity demand and income in per capita terms, effect of population is taken into account, implicitly, like in the aggregate demand studies of Bakırtaş et al. (2000), Akan and Tak (2003), Amarawickrama and Hunt (2008), Issa and Bataineh (2009), Erdoğdu (2007), Contreras (2008), Chaudhry (2010), Lee and Lee (2010), and Maden and Baykul (2012), Zaman et al. (2012). However, explicitly, positive effect of population is expected.

We expect increase in electricity demand as a result of increase in urbanization. Holtedahl and Joutz (2004) have explained the reasons as follows; "urbanization implies greater access to electricity" (Holtedahl and Joutz, 2004: 203) resulted from easy connection to the grid and also leads to the "increased use of existing appliances and purchase of new ones due to the exposure to the media and advertising typical of large cities" (Holtedahl and Joutz, 2004: 203). Among the aggregate electricity demand studies, urbanization ratio was included to the model only by Diabi (1998) and was found to have significant and positive effect, on the other hand, Bekhet and Othman (2011) have analyzed the effects of urban and rural population variables, separately and findings showed the urban population significantly increases the electricity demand. Holtedahl and Joutz (2004) have used urbanization as a proxy for economic development and changes in electricity using capital stock in the residential electricity demand model and found significant effect. Halıcıoğlu (2007) found significant and positive impact of urbanization on residential electricity demand for Turkey.

Although, "weather is perhaps the most important determinant of electricity consumption" (Diabi, 1998:17) and this argument is also supported by Kriström (2008) for energy consumption, according to Pouris (1987), Francisco (1988), Chang and Hsing (1991), and Diabi (1998), as weather may show less variation across years, this variable may not add explanatory power to the model for the studies using annual national level data. Pouris (1987), Lin (2003), and Inglesi (2010) have excluded the temperature variable from their aggregate electricity model because of use of annual national level data as well as small share of residential sector in the total electricity demand which they have thought to be more sensitive to the variation of temperature compared to other sectors. Also, "such weather variables have commonly been included in studies using regional data" (Chang and Hsing, 1991: 1252). In order to consider the effect of weather, we employ heating and cooling degree days variables. "The concept of degree days is used to evaluate energy demand for cooling and heating services as it measures the average temperature's departure from a human comfort level" (Abosedra et al., 2009: 12). "On cold days, consumers turn on the heat, and on hot days, they turn on air conditioner or a fan" (Diabi, 1998: 17), therefore, as the cooling and heating requirements increase, we expect electricity demand to increase, thus, positive coefficients on these variables. The empirical studies on aggregate electricity demand which have found positive significant effects of heating and/or cooling degree days are Hsiao et al. (1989), Nasr et al. (2000), Abosedra et al. (2009), and Fan and Hydman (2011), however, although estimation results of the studies by Kamerschen and Porter (2004), Contreras (2008), and Jamil and Ahmad (2011) showed positive coefficients for the degree days variables, all found to be insignificant.

The last variable in our model is economic uncertainty. Based on the theories of investment under uncertainty and real options, "increased uncertainty can influence the decision behavior of economic agents and cause a delay in the production and consumption decision, thereby lowering the quantity adjustment and increasing the price response after shocks" (Robays, 2012: 2). In the literature, up to our knowledge, none of the studies incorporate the economic uncertainty into the electricity demand model. However, as electricity demand is also an economic decision, we expect negative effect of economic uncertainty on the electricity demand for risk-averse agents, while if the majority of the agents are risk-neutral or risk-lover, insignificant or even positive impact may be observed assuming linear technology. According to Plante and Traum (2012), with the special focus on investment decisions, past theoretical works have defined two channels through which the economic decisions are affected by uncertainty based on the precautionary savings motive (for example, Sandmo (1970)) and real options effect (for example, Henry (1974), Bernanke (1983), Brennan and Schwartz (1985), Majd and Pindyck (1987), Brennan (1990), Gibson and Schwartz (1990), Triantis and Hodder (1990), Aguerrevere (2009), and Bloom (2009)). First channel predicts that by reducing consumption and increasing savings, higher uncertainty leads to increase in the investment. However, second channel implies reduction/delay in investment as a result of higher uncertainty based on the irreversibility of investment through real options effect because "if an investment is irreversible, increased uncertainty raises the option value of waiting to invest" (Guo and Kliesen, 2005: 679).

In order to check for robustness of our results to the different proxy measures of economic uncertainty, in our study, we consider the exchange rate volatility, industrial production volatility, stock market volatility, and oil price volatility. Exchange rate, industrial production, stock market, and oil price volatilities represent the uncertainties related to foreign trade and foreign investment, macro economy excluding the service sector, financial market, and energy market, respectively.

There are many theoretical and empirical studies that include the different types of uncertainty into their models. Turnovsky and Chattopadhyay (1998) have classified some of the theoretical models which incorporate the effect of risk on economic behavior into two groups, as partial equilibrium models of the firm (McCall (1967), Hartman (1972), Abel (1983), Pindyck (1988), Caballero (1991)) and stochastic general equilibrium growth models (Eaton (1981), Gertler and Grinols (1982), Devereux and Smith (1991), Grinols and Turnovsky (1993, 1998), Turnovsky (1993), Grinols and Turnovsky (1994), Obstfeld (1994), Smith (1996), and Corsetti (1997), and Asea and Turnovsky (1998)). The second class of "models yield a macroeconomic equilibrium in which the growth rate is related to the various sources of exogenous risk impacting the economy, and their interaction with policy variables" (Turnovsky and Chattopadhyay, 1998: 2) and Turnovsky and Chattopadhyay (1998) have claimed that the second class of models is more appropriate to build empirical macro relations between risk and growth. They have developed a theoretical model in order to consider domestic production risk, domestic fiscal risk, and external terms of trade risk and empirically applied it to the 61 developing debtor countries facing imperfect world capital market. Their findings showed the strong negative effects of monetary volatility, fiscal volatility, and terms of trade volatility on the growth rate; however, insignificant negative effect of output volatility unless considered separately. Among the empirical studies, Grier and Tullock (1989) and Caporale and McKiernan (1998) have found that growth uncertainty raises growth in line with Black's (1987) claim. Ramey and Ramey (1995), Aizenman and Marion (1993, 1997), Hnatkovska and Loayza (2005), Köse et al. (2006), Imbs (2007), and Berument et al. (2011) are the other studies that have found the negative effect of output growth volatility on the output growth. In contrast, positive impact was found by some other studies such as Kormendi and Meguire (1985) and Grier and Tullock (1989) and insignificant positive effect by Gavin and Hausman (1995). Berument et al. (2011) have also analyzed the effects of output growth volatility on the transmission variables which contributes significantly to output growth such as, total factor productivity, investment, employment, and exchange rate and they have showed that the adverse impact of growth volatility on growth is transmitted from the negative effects of volatility on total factor productivity, investment, and exchange rate. The transmission mechanisms for each of the variable were described by Berument et al. (2011) as follows; firstly, decreases in the levels of productivity and input cause decline in the total factor productivity and investment, and thus in growth; secondly, as employment level decreases, growth declines as a result of decrease in the input level for the production; thirdly, the effects of depreciation will be the increase in the foreign currency-denominated liabilities of economic debt, capital outflows, increase in the demand for foreign currency by domestic residents, possibilities of speculative attacks, price increases and output declines by increasing input costs, and also, total spending decreases as a result of confidence loss of economic agents, moreover, depreciation can lead to the government to implement contractionary policies, which all hamper economic growth. Another empirical study was performed by Grier and Perry (2000) in order to test the effects of inflation uncertainty and output growth uncertainty on inflation and output growth. They have found only significant adverse effect of inflation uncertainty on real output growth. One another interesting study was by Huang et al. (2012) for the analysis of the output growth volatility effects on income distribution. Their results showed severe effect of volatility on income inequality which is also supported by previous empirical and theoretical studies. On the other hand, Huang (2011) have found negative effect of output volatility on net savings adjusted for natural resource depletion through the positive effect of output volatility on natural resource depletion and negative effect on net savings, and accordingly, economic volatility is seen as a impediment to global sustainability.

"In a majority of empirical studies, increasing exchange rate uncertainty is found to have economically and statistically significant profitability, investment, growth, and to some degree, trade reducing effect" (Demir, 2013. 74). Based on the previous studies, Demir (2013) defined the following effects of exchange rate volatility with the associated mechanisms or reasons such as, growth effects due to the change in the relative costs of production; negative employment and investment effects as a result of reduction in the degree of credit availability from the banking system; aggregate and productivity growth effect because of low financial development; employment and growth effects by increasing inflation uncertainty, the interest rates, and wages; international trade effects due to the increase in the transaction risk; firm level effect through negative effects on firm balance sheet, net worth, sales, profits, investment risk, and planning; investment and growth effects for foreign firms based on option pricing model. Cottani, Covallo, and Khan (1990), Mendoza (1994), Gavin and Hausmann (1995), and Arratibel et al. (2011) are the empirical studies that have found adverse effects of real/nominal exchange rate volatility on growth rate. Some of the studies have analyzed the effects of exchange rate volatility on foreign trade such as Abrams (1980), Ahktar and Hilton (1984), Cushman (1983, 1988), Kenen and Rodrik (1986), Thursby and Thursby (1987), Hooper and Kohlhagen (1978), Gotur (1985), Bailey, Tavlas, and Ulan (1987), De Grauwe and Bellefroid (1987), Koray and Lastrapes (1989), Klein (1990), and Arratibel et al. (2011) among many other studies and found conflicting results for the significance and the sign of the effect. Findings of Arratibel et al. (2011) also demonstrated that lower exchange rate volatility leads to higher stocks of foreign direct investment and excess credit. On the other hand, the relation between exchange rate volatility and employment growth was investigated by Demir (2010) for the manufacturing firms of Turkey and he found negative and significant effect of exchange rate volatility on employment growth. Demir (2013) examined the effects of exchange rate volatility on the growth of manufacturing firms in the Turkey, distinguishing between domestic and foreign and between publicly traded and non-traded firms and found significant and negative effect. Another study by Bahmani-Oskooee and Xi (2011-2012) found the significant long run and short run effects of exchange rate volatility on domestic consumption, sign of the effect shows differences across the countries. Reasoning behind this finding was explained by Alexander's (1952) claim such that total consumption declines as a result of devaluation through the effects of devaluation on inflation. Alexander (1952) argued that because of inflationary effects of devaluation, income can be transfered from employees to employers/producers but as the workers' marginal propensity to consume is high compared to producers', net effect will be decline in consumption. According to Bahmani-Oskooee and Xi (2011-2012), as exchange rate serves as a determinant of consumption, volatility of exchange rate can also affect consumption.

Another measure of uncertainty used in the studies is stock market volatility. Schwert (1989), Campbell et al. (2001), Guo (2002), Alexopoulos and Cohen (2009), Bloom (2009), and Knotek and Khan (2011) have examined the effect of stock market volatility on economic growth and activity. More recently, Beetsma and Giuliodori (2012) have investigated the macroeconomic response pattern to stock market volatility and transmission changes over time. Their findings showed that there is evidence of negative response of real GDP growth which gets smaller over time and although the contributions of deteriorations in consumption and investment growth on the response of real GDP growth is significant for the earlier periods, only slowdown in investment growth was found to be the main channel for the later periods.

We can consider the changes in oil price volatility as an external energy market uncertainty affecting the economies all around the world. Because of the risk exposed by the increase in oil price volatility on the producers and industrial consumers, the investments in oil extraction industry and the investment decisions in physical capital on natural gas or oil can be affected according to Pindyck (2004) and Pourshahabi et al. (2012). Past studies have shown that through its negative effect on investment decisions and due to the constraints on the sectoral shift of factors of production, energy-price volatility affects productivity and economic growth adversely, such as Boyd and Caporale (1996), Ferderer (1996), Hamilton (2003), and Jiménez-Rodriguez and Sánchez (2005). Arize (2000) claimed that negative impact of increase in oil price volatility on economic activity can lead reduction in energy demand or cause interfuel substitutions. Further, unfavourable effects of oil price volatility on economy at macroeconomic and microeconomic levels was discussed and shown, theoretically and empirically by Bernanke (1983), Hamilton (1988), Lee et al. (1995), Guo and Kliesen (2005), Huang et al. (2005), Bredin et al. (2008, 2009), Cologni and Manera (2009), Rafiq et al. (2009), Elder and Serletis (2010), Chen and Hsu (2012), Plante and Traum (2012), and Pourshahabi et al. (2012). Among these studies, Elder and Serletis (2010) have defined the reasons for the asymmetric effects of oil prices on the economic activity, such as frictions as a result of costly reallocation of specialized labor and capital across economic sectors following Davis (1987) and Hamilton (1988) and another reason was explained based on the theories of investment under uncertainty and real options to be the unwillingness of the firms for investment and unwillingness of the consumers for the spending on the illiquid durables due to the increased uncertainty following Henry (1974) and Bernanke (1983). "The mechanisms described by Bernanke (1983) and Hamilton (1988) may cause both oil price increases and decreases to be contractionary in the short run" (Bredin et al., 2008: 1). By employing multivariate threshold autoregressive model, Huang et al. (2005) have found greater explanatory power of oil price volatility on output change and stock returns after some threshold level of oil price volatility which varies across countries according to the imported oil dependence and the existence of energy saving technology. On the other hand, from the estimation results of Markov–Switching (MS) regime autoregressive models, Cologni and Manera (2009) have concluded that the effect of oil price volatility on output growth has mitigated over time as a result of energy efficiency improvements and better management of external supply and demand shocks by fiscal and monetary authorities. Chen and Hsu (2012) have empirically showed that the international trade is adversely affected by the oil price volatility and therefore, higher oil price volatility leads deglobalization. Energy efficiency was illustrated to be an ineffective tool for the mitigation of the negative impacts of oil price volatility on the international trade. Plante and Traum (2012) have analyzed the theoretical effects of changes in oil price volatility in general equilibrium setting using real business cycle model. They have identified three factors that affect the response direction of investment spending, spending on durables, and real GDP to an increase in oil price volatility: the degree of consumption smoothing, elasticity of substitution between durables and oil, substitutability degree of firms away from oil in their production. Based on realistic calibrations, they have found negative effect of an increase in oil price volatility on durable spending, whereas, stimulating effects on investment and real GDP regardless of irreversible capital and durable investment decisions.

Weller and Fields (2011) have discussed that because of increased energy price volatility, households, firms, businesses, and government policy makers cannot react to rising energy prices by investing in energy efficiency and by switching to alternative energy sources, instead, they delay spending, energy-saving investment, and other investments. However, they have claimed and observed that households increase their savings. Further, all these, according to Weller and Fields (2011), hamper economic growth and lead jump in unemployment. In order to mitigate the effects of high volatility, suggestions of Weller and Fields (2011) are the incentives for the diversification of energy sources and energy efficiency improvement, as both reduces the share of energy spending and thus decreases the vulnerability of economy to volatility increases.

Among energy studies, there is not so much study that analyzes the effect of economic uncertainty. The economic uncertainty was incorporated into the energy models by very few energy studies such as Molls (2000), Radchenko (2005), Kellogg (2010), Görmüş (2012), Pourshahabi et al. (2012), and Romano and Scandurra (2012). In the context of dynamic discrete choice model, Molls (2000) investigated if sunk costs and oil price volatility have any significant impact on oil production activities and his finding suggested positive but insignificant effect of oil price volatility on the probability of production, moreover, sunk cost was found to be an important determinant. Radchenko (2005) examined the effects of oil price volatility on the gasoline price asymmetry and found negative relation between them. Kellogg (2010) developed a dynamic model of firms' drilling investment timing problem to investigate the response of investment in oil well to the implied oil price volatility and results exhibited that firms decrease drilling activities when the implied oil price volatility is higher. The stock market volatility effect on the returns of energy companies' stocks was analyzed by Görmüş (2012) and except for the stocks of solar company, insignificant relation was obtained. Romano and Scandurra (2012) have explored the effects of oil price volatility on the asymmetry of industrial gasoline price and Platt's price volatilities on the asymmetry of retail gasoline price. Findings showed the decline in the degree of asymmetry for the periods with large price volatility. Pourshahabi et al. (2012) is one of the energy study which incorporates the effect of oil price volatility measured by using EGARCH model in their petroleum consumption model. They have found negative and significant effect of oil price volatility on the petroleum consumption for OECD countries over the period from 1980 to 2008. Based on this finding, against the costs associated with the oil price volatility, some of their suggestions are hedging and increase the diversity of energy sources.

In electricity demand modeling, another important issue that needs attention is the distinction between long run and short run effects of economic factors, because electricity demand may not adjust to its equilibrium level immediately after a shock to one of its determinant due to the frictions, habit formation, inertia, adjustment costs associated with the replacement of the existing capital stock and addition of new capacity, price expectations, and lack of information. In the short run, as stocks of electrical appliances, equipment, and machines, and other factors of production are fixed, only the factors that lead to changes in utilization rate of fixed electrical equipment stock determines the electricity demand; however, in the long run, size of stock and efficiency of electrical appliances, equipment, and machines can change as a result of change in the economic factors. Also, "producers often make decisions on the basis of expected prices so that their response to relative price changes is not immediate" (Considine and Mount, 1984: 438). Therefore, demand cannot adjust to the long run equilibrium levels instantaneously after a change in one of the economic factors. "This recognition actually calls for a dynamic model, where the difference between the short run and the long run is tackled explicitly" (Olsen and Roland, 1988: 16). Due to the lack of information on capital stocks and other fixed inputs, Houthakker and Taylor (1970) have introduced the flow adjustment model which is based on the partial adjustment mechanism. Olsen and Roland (1988) have critized this model because of the ignorance of the interactions with markets for other goods, ad hoc specification as it does not explain the factors determining the capital adjustment process and implicit assumption of constant capital utilization rate by not explicitly modeling the relation between capital stock and energy use. Another critism from Bohi (1981) and Bohi and Zimmerman (1984) is the erratic and unreliable elasticity estimates produced by the dynamic reduced form models which include the lagged dependent variable into the model. As mentioned by Amusa et al. (2009), earlier studies after the works of Houthakker (1951) and Fisher and Kaysen (1962) did not consider the time series properties of the data and in order to differentiate between the long run and short run effects of the determinants of electricity demand, they have heavily employed partial adjustment model. However, "in the 1980s, the stationarity of the economic variables assumed in the standard estimation methods was questioned" (Bhattacharyya and Timilsina, 2009: 31). According to Bhattacharyya and Timilsina (2009), most of the variables employed in energy demand analysis was suggested to be integrated of order 1, I(1) and therefore, there can be possibility of spurious relation problem associated with the non-stationary data. This problem leads to the introduction of cointegration concept to the literature, and the emergence of many advanced techniques in this area, such as cointegration tests and error correction models. "This development in the econometric analysis has significantly influenced the energy demand studies in the 1990s and brought the *unit root revolution*" (Bhattacharyya and Timilsina, 2009: 31). In the aggregate electricity demand studies under our examination, following dynamic models were employed: distributed lag model (Pouris (1987), Whittaker and Barr (1989)); partial adjustment model (Hsiao et al. (1989), Diabi (1998), Nasr et al. (2000), Erdoğdu (2007), Bhargava et al. (2009)); error correction model (Bakırtaş et al. (2000), Nasr et al. (2000), Al-Faris (2002), Akan and Tak (2003), Fatai et al. (2003), Amarawickrama and Hunt (2008), Inglesi (2010), Alter and Syed (2011), Bekhet and Othman (2011), Jamil and Ahmad (2011), Maden and Baykul (2012)); autoregressive distributed lag (ARDL) model (De Vita et al. (2006), Amusa et al. (2009), Bhargava et al. (2009), Khan and Qayyum (2009), Sohaili (2010), Ekpo et al. (2011), Zaman et al. (2012), Ziramba and Kavezeri (2012)).

In the empirical application sections, we present the dynamic models, both partial adjustment model and error correction model, explicitly. In the next section, we model volatilities of important economic variables affecting the electricity demand.

CHAPTER 5

MODELING VOLATILITIES OF IMPORTANT ECONOMIC VARIABLES AFFECTING ELECTRICITY DEMAND

Effects of the volatilities of important economic variables cannot be ignored on the energy sector. As already mentioned in Chapter 4, based on the theories of investment under uncertainty and real options, "increased uncertainty can influence the decision behavior of economic agents and cause a delay in the production and consumption decision, thereby lowering the quantity adjustment and increasing the price response after shocks" (Robays, 2012: 2). Also according to Weller and Fields (2011), because of increased energy price volatility, households, firms, businesses, and government policy makers cannot react to rising energy prices by investing in energy efficiency and by switching to alternative energy sources, instead, they delay spending, energy-saving investment, and other investments. In the literature, up to our knowledge, none of the studies incorporate the economic uncertainty into the electricity demand model. However, as electricity demand is also an economic decision, we expect significant effect of economic uncertainty on the electricity demand. Most of the empirical studies have found adverse growth effects of exchange rate volatility, growth volatility, stock market volatility and oil price volatility. In this study, we consider both real effective and nominal effective exchange rate volatility, in order to determine if there is any difference when we include the effect of inflation differentials between countries.

In this section, we discuss first the method that we employ for volatility modeling and introduce the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models designed to model and forecast volatility (or conditional variance) of a variable and their variants. Section 5.1 illustrates the modeling procedure and different specifications for GARCH models. In Section 5.2, in order to obtain volatility measurement, we apply ARCH/GARCH models to various series: real exchange rate calculated using PPI, real exchange rate calculated using CPI, industrial production index, crude oil spot price, nominal exchange rate and İstanbul Stock Exchange-100 index.

5.1. Econometric Models of Volatility

The main characteristic of volatility is such that it is unobservable directly unlike other economic variables such as prices and quantities. Despite this, proxy measures for volatility can be derived by using those variables. Asset returns are the most volatile economic variables which are closely and widely followed by economic agents. Common features of asset returns volatility have been listed by Tsay (2002) as follows: clustering behavior, rare jumps, stationarity and asymmetry. Franses and van Dijk (2000) have emphasized that the time varying nature of volatility is recognized by Mandelbrot (1963), however, modeling this property is considered in ARCH models beginning with Engle (1982). Mandelbrot (1963) observation is: “large changes tend to be followed by large changes -of either sign- and small changes tend to be followed by small changes..”. Various volatility models are built to capture these characteristics. However, as emphasized by Özer and Türkyılmaz (2005) in order to measure volatility, different methods are employed in the literature such as, variance or standard error of observed variable, moving average of absolute change in variable, survey based proxies obtained from survey of expectations using conditional forecast error variance and moving standard deviation of variable of interest. Özer and Türkyılmaz (2005) have mentioned also that as, all these methods to measure volatility contain both predictable and unpredictable variability, they cannot distinguish between variability and volatility. Therefore, some studies employ GARCH models to proxy the volatility by conditional error variance. We focus on univariate fixed parameter models in our study and give some brief information on GARCH models and their variants.

"ARCH models were first introduced by Engle (1982)" (Franses and van Dijk, 2000: 135). Bollerslev (1986) and Taylor (1986) generalized them as GARCH models. Engle, Lilien and Robins (1987) have extended Engle's ARCH model as ARCH-M model to allow impact of the conditional variance on the mean as mentioned by Enders (2004). Nelson (1990) introduces IGARCH model by restricting the sum of the coefficients of GARCH process to equal to one to consider the persistency of volatility shocks. In order to capture asymmetric effects between positive and negative asset returns, Nelson (1991) proposes EGARCH model. TARCH and Threshold GARCH were introduced by Zakoïan (1994) and Glosten, Jaganathan and Runkle (1993) to account for leverage effects. All these models were designed to model and forecast volatility (or conditional variance) of a variable. Last two models also allow for asymmetry in volatility. They have extent use especially in financial time series analysis, however as pointed out by Andersen, Bollerslev, Christoffersen and Diebold (2005), applications of volatility modeling are extended to other fields. Andersen, Bollerslev, Christoffersen and Diebold (2005) have provided some examples related to the various use of volatility modeling tools in different areas. The G(ARCH) models have many wide range of specifications providing a rich class of possible parameterizations of heteroscedasticity under various distributional assumptions: EGARCH, ARCH-M, IGARCH, GJR-GARCH, TARCH, STARCH, AARCH, NARCH, MARCH, SWARCH, SNPARCH, APARCH, TAYLOR-SCHWERT, FIGARCH, FIEGARCH, Component ARCH, Asymmetric Component ARCH, SQGARCH, CESGARCH, Student t- ARCH, GED-GARCH, SPARCH (Tsay, 2002: 79; Enders, 2004: 140-143; Verbeek, 2004: 300). The modeling procedure for GARCH models can be explained by the following steps (Enders, 2004: 119-120, 146-150; Tsay, 2002: 86-90);

i. First we build an ARMA (p, q) or a regression model to remove the linear dependence in the data. Box-Jenkins model selection procedure is followed for ARMA (p, q) model. We select the lag based on information criteria, autocorrelation function and partial autocorrelation function. We perform the estimation assuming constant variance by OLS and select the best model for the series such that the autocorrelation function and partial autocorrelation function of residuals need to be indicator of white noise residuals. In other words, there should not be any remaining autocorrelation in the residuals of the model. Assuming constant variance may result in inefficient estimates if there is a time varying variance. So we add the time varying variance into estimation. In this context, we estimate various specifications of ARCH models. The details of different specifications are given in the remaining part of this section.

ii. As a second step, we test the presence of ARCH effects by ACF and PACF of squared residuals obtained from the estimation of above model and performing the (G)ARCH LM test of Engle (1982) (and Bollerslev (1986)) by regressing the squared residuals obtained from the ARMA(p,q) model on the lagged values of squared residuals as shown below;

$$\hat{\varepsilon}_t^2 = \alpha_0 + \alpha_1 \hat{\varepsilon}_{t-1}^2 + \alpha_2 \hat{\varepsilon}_{t-2}^2 + \ldots\ldots\ldots\ldots + \alpha_m \hat{\varepsilon}_{t-m}^2, \; t=m+1,\ldots,T \tag{5.1}$$

where, $\hat{\varepsilon}_t^2$ are the squared residuals obtained from the estimation of ARMA(p,q) model. From this auxiliary regression, we obtain the following statistic statistic in order to test if the slope coefficients are jointly equal to zero; $T * R^2 \sim \chi_m^2$ (asymptotically). From these tests, if there is evidence of ARCH effects, we use the ARCH specifications which are explained below.

iii. In the last step, we model the volatility in the variable using different specifications of GARCH models and then, perform estimation by Maximum Likelihood (MLH) estimation method. In the standardized residuals of the proper models, there should not be any remaining autocorrelation, conditional volatility and leverage effects. Therefore, we make diagnostic checking (PACF of standardized residuals, PACF of squared standardized residuals, ARCH-LM test, normality test by quantile to quantile plot and leverage effects test) for the models and we choose the one that does not violate restrictions if there is any, and among the proper models the choice depend upon the information criteria, Log likelihood and forecast performance. Various specifications for ARCH/GARCH models are explained below.

"The first systematic approach for modeling volatility (conditional variance) was proposed by Engle (1982) as ARCH (q) model in which conditional variance depends on the past squared errors of mean equation shown below" (Franses and van Dijk, 2000: 139);

Mean Equation: $y_t = \mu + \varepsilon_t$ (5.2)

Conditional (ARCH(q)) Variance Equation: $h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$ (5.3)

where, $\varepsilon_t \sim iid(0, h_t)$.

"For covariance stationary ARCH process, the sum of the α_i parameters in equation (5.3) must be less than unity" (Verbeek, 2004: 298). Tsay (2002) emphasized that ARCH processes have heavier tail distribution compared to that of normal distribution and listed the weaknesses of ARCH models as follows: symmetric effects of positive and negative shocks on volatility, nonnegativity constraints, restrictions for finite fourth order moment, possibility of volatility overprediction and insufficient description of the conditional variance behavior.

Bollerslev (1986) proposed an extension of ARCH process called GARCH (q, p) model adding lagged values of conditional variance to the above variance equation specification. Conditional variance equation of this specification can be written as (Enders, 2004: 118);

$$h_t = \omega + \sum_{j=1}^{q} \beta_j h_{t-j} + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 \quad (5.4)$$

Tsay (2002) noted that same tail distribution property and weaknesses are observed in GARCH (q, p) process as in the ARCH model, however, superiority of GARCH model stated by Bera and Higgins (1998) and Enders (2004) is the parsimonious representation of a higher order ARCH model providing a simpler conditional variance specification which is much easier to identify and estimate. All the coefficients in (5.4) must be positive and for a finite variance, all characteristic roots of (5.4) must lie inside the unit circle (Enders, 2004: 118). As demonstrated by Bollerslev (1986), for stationarity of GARCH process, sum of the ARCH and GARCH coefficients ($\alpha + \beta$) must be smaller than one. In IGARCH specification, we impose the constraint that ($\alpha + \beta$) is equal to one, indicating the persistency of volatility shocks. This result is often observed in high frequency financial data (Franses and van Dijk, 2000: 142). IGARCH models can be seen as unit-root GARCH models as described by Tsay (2002). Nelson (1991) and Nelson (1990) showed that this yields parsimonious strictly stationary process representation for the distribution of an asset's return (Franses and van Dijk, 2000: 143; Enders, 2004: 140).

Engle, Lilien and Robins (1987) have extended the ARCH model to allow the conditional variance to affect the mean and call the model as ARCH-M model. Bera and Higgins (1998) have pointed out that ARCH-M model is employed to test and estimate a time varying risk premium. We can represent the means equations for this specification as follows;

$$y_t = \mu + \tau h_t + \varepsilon_t \tag{5.5}$$

$$y_t = \mu + \tau\sqrt{h}_t + \varepsilon_t$$

$$y_t = \mu + \tau \log(h_t) + \varepsilon_t$$

Tsay (2002) stated that existence of risk premium implies serial correlation in the y series. The risk premium is an increasing function of the conditional variance (Enders, 2004: 129). A positive τ indicates that the return is positively related to its past volatility (Tsay, 2002: 101). Risk-return tradeoff can be measured by $\hat{\tau}$.

In order to model volatility asymmetry, various models have been proposed as notified by Andersen, Bollerslev, Christoffersen and Diebold (2005). In their paper, they have listed the studies of Black (1976), Christie (1982), Nelson (1991), Engle and Ng (1993), Glosten, Jaganathan and Runkle (1993), Zakoïan (1994), Campbell and Hentschel (1992), Hentschel (1995), Bekaert and Wu (2000) and Engle (2001) which focus on the importance of considering leverage effects and modeling issues. Below, some brief information on TARCH, Threshold GARCH and EGARCH models are given.

Zakoïan (1994) and Glosten, Jaganathan and Runkle (1993) have introduced TARCH and Threshold GARCH models to account for leverage effects, i.e., positive and negative shocks have asymmetric impact in conditional standard deviation and variance equations, respectively. In general, the specification for the conditional variance is as follows incorporating an additional ARCH term conditional on the sign of past innovation (Enders, 2004: 141; Andersen, Bollerslev, Christoffersen and Diebold, 2005:21);

$$h_t = \alpha_0 + \sum_{j=1}^{q} \beta_j \, h_{t-j} + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{k=1}^{r} \gamma_k \, \varepsilon_{t-k}^2 \, d_{t-k} \qquad (5.6)$$

where $d_t = 1 \; if \; \varepsilon_t$<0 and 0 otherwise.

Positive shocks influence the conditional volatility by the magnitude of α_i whereas; negative shocks have an impact of $\alpha_i+\gamma_k$. If $\gamma_k > 0$, negative shocks increase volatility more than positive shocks and there exists a leverage effect of order k. If $\gamma_k = 0$, the shocks have no asymmetric effect. As in the simple GARCH models, here also nonnegativity constraint must be considered.

Another model to account for the asymmetry in the volatility is EGARCH model proposed by Nelson (1991). The variance equation is as follows (Enders, 2004: 142);

$$\ln(h_t) = \alpha_0 + \sum_{j=1}^{q} \beta_j \ln(h_{t-j}) + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} \right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sqrt{h_{t-k}}} \qquad (5.7)$$

where, $\left| \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} \right|$ is the absolute value of lagged standardized disturbance. The significant difference from the TARCH or TGARCH specifications is that non-negativity constraint is not necessary in this specification. However, "one disadvantage of EGARCH model put forward by Engle and Ng (1993) is the overestimation possibility of outliers effects on volatility" (Herwartz, 2004: 204). Standardization of the residuals as suggested by Nelson (1991) makes the interpretation of the size and persistence of shocks easy (Enders, 2004: 142). The model allows for asymmetric effects through $\sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}}$ noted by Verbeek (2004). The positive shocks have an impact of $\alpha_i + \gamma_k$. On the other hand, negative shocks have $\alpha_i - \gamma_k$ effect on the logarithm of the conditional variance. In order to have asymmetric effect, the coefficient γ_k must be different from zero. The incorporation of the restriction $\left| \sum_{j=1}^{q} \beta_j \right| < 1$ guarantees the non-explosion of log of the conditional variance equation (Nelson, 1991: 352). Originally, Nelson assumes that the residuals follow a Generalized Error distribution.

Power ARCH model proposed by Taylor (1986), Schwert (1989) and Ding et al. (1993) was designed to model standard deviation and also leverage effects can be considered with additional parameters. "The PARCH equation is given by the following expression for asymmetric model" (Zivot, 2008: 18);

$$h_t^{\delta/2} = \alpha_0 + \sum_{j=1}^{q} \beta_j h_{t-j}^{\delta/2} + \sum_{i=1}^{p} \alpha_i \left(|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i}\right)^{\delta} \qquad (5.8)$$

where δ is the power parameter. There is evidence of asymmetry, if γ_i is statistically significant.

“Component ARCH was first introduced by Ding and Granger (1996) and Engle and Lee (1999) have made some further modifications in the model” (Bauwens and Storti, 2008: 2). “It allows one to distinguish between transitory and permanent components leading to better description of volatility dynamics” (Wei, 2009: 63). “Engle and Lee (1999) have shown that symmetric component GARCH (1, 1) model is a restricted version of GARCH (2, 2) model” (Colacito, Engle, Ghysels, 2010: 7). “Variance equations for short run and long run components for symmetric component GARCH (1, 1) model are given as follows, respectively” (Lee, Lin and Liu, 2010:101);

$$\begin{aligned}&\text{Transitory component: } h_t - q_t = \beta(h_{t-1} - q_{t-1}) + \alpha(\varepsilon_{t-1}^2 - q_{t-1})\\&\text{Permanent component: } q_t = \omega + \rho(q_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - h_{t-1})\end{aligned} \tag{5.9}$$

Combining equations for transitory and permanent components yields a variance equation which is a restricted GARCH (2, 2) model as proved previously by Engle and Lee (1999). Leverage effects may be taken into account in the transitory equation by a TARCH model specification.

There are many other extensions of GARCH models. However, in our study, we focus only on univariate GARCH models mentioned above. In the remaining part of this subsection, we discuss the estimation of GARCH models. There are various parametric estimation methods based on Least Squares, Generalized Method of Moments (GMM) and Maximum Likelihood methods. “Rich, Raymond and Butler (1991) have considered the GMM estimation of ARCH model” (Bera and Higgins, 1998: 48). On the other hand, Ordinary Least Squares (OLS) estimation method can be employed, but, it leads to inefficient estimator. To overcome this problem, one can use Feasible Generalized Least Squares (FGLS) method. In some of the ARCH model specifications, nonnegativity constraint needs to be considered. “When estimate has negative components, volatility predictions can be negative” (Francq and Zakoïan, 2010: 135). Constrained OLS estimator can solve the problem of negative volatility predictions as mentioned by Francq and Zakoïan (2010). Other method which is preferred to OLS and FGLS is Quasi-Maximum Likelihood (QMLE) method that provides consistent and asymptotically normal estimators for strictly GARCH processes under mild regularity conditions, “but with no moment assumptions on the observed process even though the likelihood function is incorrectly specified” (Francq and Zakoïan, 2010: 141; Verbeek, 2004: 301). “However, according to González-Rivera, QMLE can produce inefficient estimator and they propose a semiparametric approach based on the maximization of log likelihood function” (Bera and Higgins, 1998: 48). In our study, estimation of GARCH models is performed by MLH method under different distributional assumptions. Below, “for a simple GARCH/ARCH model, log likelihood functions are given under assumptions of normal distribution, Student’s t distribution and Generalized Error distribution, respectively” (Enders, 2004: 140);

$$lnL = -\frac{T}{2}\ln(2\pi) - 0.5\sum_{t=1}^{T} lnh_t - 0.5\sum_{t=1}^{T}\left({\varepsilon_t^2}/{h_t} \right) \quad (5.10)$$

$$lnL = -\frac{T}{2}\ln\left(\frac{\pi(v-2)\Gamma(v/2)^2}{\Gamma((v+1)/2)^2}\right) - 0.5\sum_{t=1}^{T} lnh_t - 0.5(v+1)\sum_{t=1}^{T} ln\left(1 + {\varepsilon_t^2}/{h_t(v-2)}\right) \quad (5.11)$$

$$lnL = -\frac{T}{2}\ln\left(\frac{\Gamma(1/r)^3}{\Gamma(3/r)(r/2)^2}\right) - 0.5\sum_{t=1}^{T} lnh_t - \sum_{t=1}^{T}\left({\Gamma(3/r)\varepsilon_t^2}/{h_t\Gamma(1/r)} \right)^{r/2} \quad (5.12)$$

where where $v > 2$ is the degree of freedom and $r > 0$ is the tail parameter.

5.2. Modeling Volatilities of Important Economic Variables in Energy Demand

In this section, our aim is to obtain volatility measurement and for this purpose, we apply ARCH/GARCH models to various series: real exchange rate calculated using PPI (REEXP), real exchange rate calculated using CPI (REEXC), industrial production index (IPI), crude oil spot price (POIL), nominal exchange rate (NEXCR) and İstanbul Stock Exchange-100 index (ISE100). Conditional variances are used as proxy for volatility. First, we give brief information on data and then in section 5.2.2, we present the estimation results of ARCH/GARCH models.

5.2.1. Data

Data frequency, time periods, summary statistics and data sources are given in Table 5.1. We use seasonally unadjusted time series. Different from nominal exchange rate, real exchange rate indices include the inflation differentials between Turkey and the countries under consideration. For the calculation of real effective exchange rate indices, one can refer to Saygılı et al. (2010). REEXP is the real effective exchange rate index calculated at producer's prices (whole sale prices before 2005), 1995=100; REEXC is the real effective exchange rate index calculated at consumer's prices, 1995=100; IPI is the industrial production index with base year 1997=100; POIL is the spot price of crude oil ($/barrel); nominal exchange rate (NEXCR (TL)) is calculated as a weighted average of exchange rates which are average of buying and selling rates obtained from Central Bank of Republic of Turkey (CBRT) Database. Weights are the trade shares of each country. Trade shares are calculated using Turkish Statistical Institute (TURKSTAT) data on foreign trade of Turkey with each country; ISE100 index is taken according to closing prices (January 1986 =1). All the series seem to have nonnormal distribution with one exception: IPI series.

Figure 5.1 and 5.2 show the plot of the series. As we can see from the graph of REEXP series, there is no clear pattern in the trend. There are periods of appreciation and depreciation. This is also valid for REEXC. There is increasing trend in the IPI series. Graph of crude oil spot price shows that there is an upward pattern in the trend after 2002; and also there are periods of price spikes. In the graph of nominal weighted exchange rate, upward pattern in the trend before 2002 is observed; and afterwards, there are periods of appreciation and depreciation. Although there is an upward trend in the ISE100 series; there are periods of increase and decrease. All the series seem to be nonstationary. Most of the formal unit root tests in Table 5.2 and correlogram of the series also support this claim. Therefore, we continue our analysis with change in the series proxied by the logarithmic difference of the series. Plots of logarithmic differenced series are given in Figures 5.3 and 5.4. From figures, we observe that series seem to fluctuate around a constant mean with a constant variance implying that logarithmic differenced series are covariance stationary. Histograms and summary statistics for logarithmic differenced series are shown in Figures A.1 and A.2. Only DLIPI_DSA series exhibits normal distribution. Correlogram and most of the unit root tests in Table 5.3 also support that in the logarithmic differenced series there is no evidence of unit roots. Therefore, we can treat them as stationary processes. As the stationarity criterion is satisfied, we continue with the estimations of models for each series from the autoregressive family. In the next section, we present estimation and diagnostic tests results of the models estimated.

Table 5.1 Summary Statistics and Data Sources

Series	**REEXP**	**REEXC**	**IPI**	**POIL**	**NEXCR**	**ISE100**
Frequency	Monthly	Monthly	Quarterly	Monthly	Weekly	Monthly
Time Period	1980M01-2010M05	1980M01-2010M05	1980Q1-2006Q4	1985M01-2010M12	1990W01-2010W50	1987M11-2011-M01
Observations	365	365	108	312	1094	279
Mean	122.9652	126.8274	78.13333	32.75679	0.341101	14536.56
Median	117.0000	122.2000	75.05000	21.59500	0.279353	5451.840
Maximum	188.5000	194.1000	142.6000	133.1800	0.774285	68787.18
Minimum	81.50000	78.00000	28.70000	9.410000	0.001172	3.798640
Std. Dev.	20.54930	26.22609	30.08493	24.06677	0.295582	18450.11
Skewness	0.321468	0.572513	0.236922	1.709039	0.055700	1.185302
Kurtosis	2.093298	2.570342	2.132144	5.473339	1.206166	3.206786
Jarque-Bera	18.78952	22.74699	4.399661	231.4087	147.2455	65.82682
Probability	0.000083	0.000011	0.110822	0.000000	0.000000	0.000000
Sum	44882.30	46292.00	8438.400	10220.12	373.1640	4055699.
Sum Sq. Dev.	153707.6	250362.1	96846.04	180134.1	95.49405	9.46E+10
Data Source	CBRT EDDS	CBRT EDDS	CBRT EDDS	IEA Database	Author's own calculation	CBRT EDDS

Note: EDDS and IEA are abbreviations for Electronic Data Delivery System and International Energy Agency.

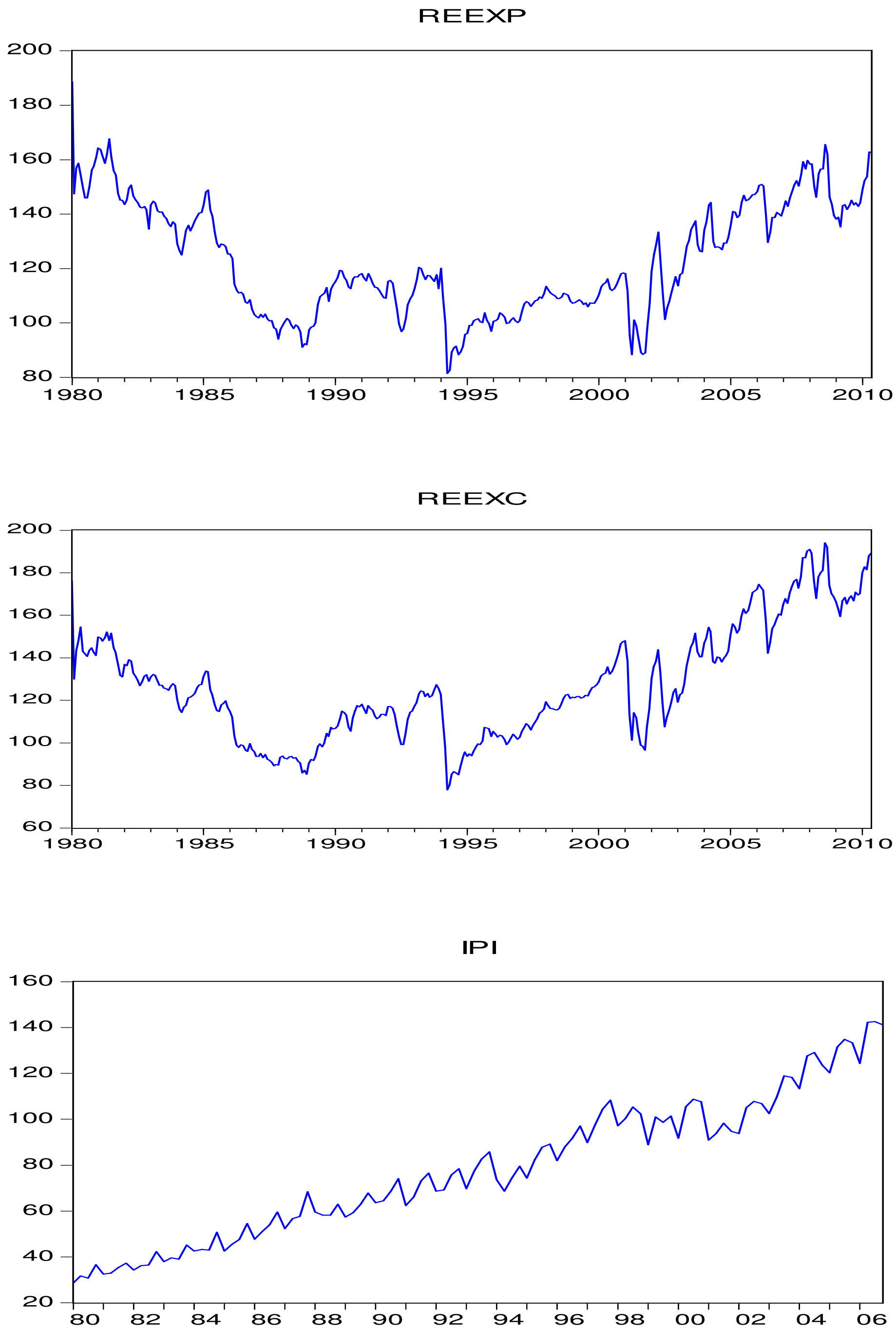


Figure 5.1 Real Exchange Rate and Industrial Production Indices Series

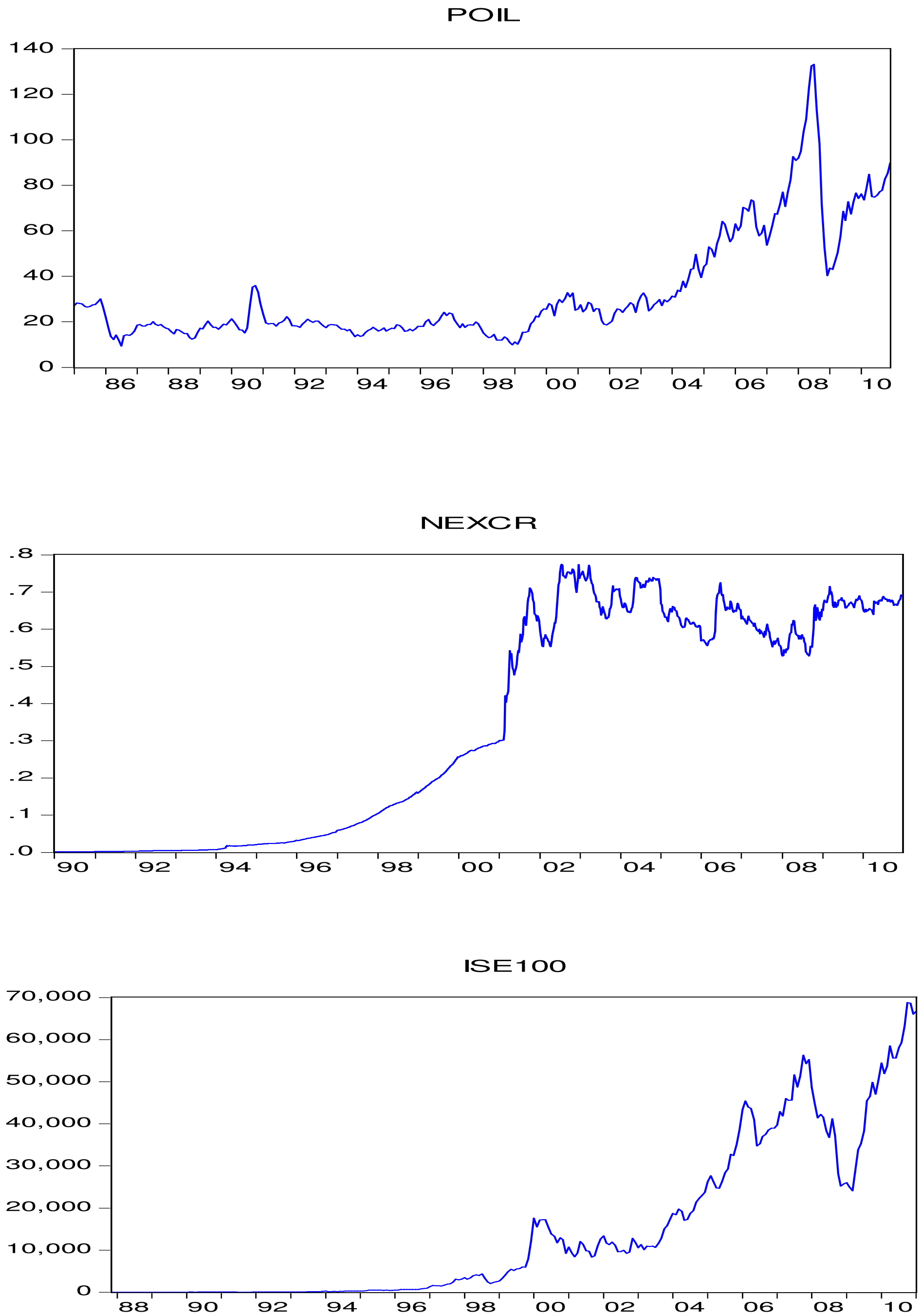


Figure 5.2 Crude Oil Spot Price, Nominal Exchange Rate and ISE 100 Index Series

Table 5.2 Unit Root Tests for Variables in Levels

Tests /Series	REEXP	REEXC	IPI	POIL	NEXCR	ISE100
Augmented Dickey-Fuller test	-1.793 (0.38)	-1.503 (0.53)	-2.640 (0.26)	-3.246* (0.08)	-1.547 (0.81)	-1.968 (0.62)
Elliott-Rothenberg-Stock DF-GLS test	-0.847	-1.025	-2.757*	-2.435	-1.340	-1.523
Phillips-Perron test	-2.974** (0.04)	-1.646 (0.46)	-6.239*** (0.00)	-2.484 (0.34)	-1.663 (0.77)	-1.405 (0.86)
KPSS test	0.52**	1.07***	0.08	0.43***	0.46***	0.39***
Elliott-Rothenberg-Stock test	26.92	12.13	0.008***	7.801	25.07	14.70
Ng-Perron test						
MZa	-0.990	-2.102	-285.4***	-13.50	-3.633	-7.066
MZt	-0.689	-1.009	-11.92***	-2.492	-1.339	-1.617
MSB	0.696	0.480	0.042***	0.185*	0.369	0.229
MPT	24.02	11.52	0.387***	7.366	24.94	13.29

Note: The null hypothesis is that the series is a unit root process except for Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. An intercept (intercept and trend) is included in the test equations (for IPI, POIL, NEXCR and ISE100). P-values are provided in parentheses.The lag length was selected by using the Schwarz Information Criteria. For Newey-West bandwidth selection, Bartlett kernel was used. Elliott-Rothenberg-Stock DF-GLS test critical values for REEXP and REEXC, IPI, POIL, NEXCR, ISE100 series at (1%, 5%, 10%) significance levels are (-2.571348, -1.941699, -1.616114), (-3.5838, -3.0332, -2.7430), (-3.471, -2.908, -2.6015), (-3.48, -2.89, -2.57), (-3.4675, -2.915, -2.61375), respectively. Asymptotic critical values of KPSS test at 1%, 5% and 10% significance levels for test equations with constant (with constant and trend) are given as 0.739 (0.216), 0.463 (0.146) and 0.347 (0.119), respectively. (1.976, 3.24425, 4.45375), (4.2432, 5.6416, 6.7956), (3.9996, 5.6376, 6.8768), (3.96, 5.62, 6.89), (4.01445, 5.6442, 6.87185), are the critical values of Elliott-Rothenberg-Stock test at (1%, 5%, 10%) significance levels for REEXP and REEXC, IPI, POIL, NEXCR, ISE100 series, respectively. Asymptotic critical values of Ng-Perron test for test equations with intercept (intercept and trend) are -13.8 (-23.8), -8.1 (-17.3) and -5.7 (-14.2) for Mza statistics; -2.58 (-3.42), -1.98 (-2.91), -1.62 (-2.62) for MZt statistics; 0.174 (0.143), 0.233 (0.168), 0.275 (0.185) for MSB statistics; and 1.78 (4.03), 3.17 (5.48) and 4.45 (6.67) for MPT statistics at 1%, 5% and 10% significance levels, respectively. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%.

Table 5.3 Unit Root Tests for Variables in Logarithmic Differences

Tests /Series	DREEXP	DREEXC	DLIPIDSA[1]	DLPOIL	DLNEXCR	DLNISE100
Augmented Dickey-Fuller test	-16.2*** (0.00)	-12.5*** (0.00)	-5.4*** (0.00)	-13.8*** (0.00)	-10.5*** (0.00)	-7.7*** (0.00)
Elliott-Rothenberg-Stock DF-GLS test	-0.245	-0.232	-1.191	-12.8***	-10.03***	-6.17***
Phillips-Perron test	-16.9*** (0.00)	-16.82*** (0.00)	-13.4*** (0.00)	-13.5*** (0.00)	-27.88*** (0.00)	-12.67*** (0.00)
KPSS test	0.387*	0.341	0.232	0.140	1.909***	0.238
Elliott-Rothenberg-Stock test	8.054	9.033	1.21***	0.19***	0.17***	0.36***
Ng-Perron test						
MZa	0.226	0.292	0.418	-140.3***	-137.7***	-55.2***
MZt	0.313	0.439	0.317	-8.374***	-8.294***	-5.252***
MSB	1.387	1.506	0.757	0.059***	0.060***	0.095***
MPT	107.3	127.3	38.32	0.175***	0.182***	0.447***

Note: The null hypothesis is that the series is a unit root process except for Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. An intercept is included in the test equations. P-values are provided in parentheses.The lag length was selected by using the Schwarz Information Criteria. For Newey-West bandwidth selection, Bartlett kernel was used. Elliott-Rothenberg-Stock DF-GLS test critical values for DREEXP and DREEXC, DLIPI_DSA, DLPOIL, DLNEXCR, DLNISE100 series at (1%, 5%, 10%) significance levels are (-2.571348, -1.941699, -1.616114), (-2.58853, -1.944105, -1.614596), (-2.572443, -1.941850, -1.616015), (-2.567089, -1.941115, -1.616503), (-2.573398, -1.941982, -1.615929), respectively. Asymptotic critical values of KPSS test at 1%, 5% and 10% significance levels for test equations with constant are given as 0.739, 0.463 and 0.347, respectively. (1.976, 3.24425, 4.45375), (1.9472, 3.1142, 4.1812), (1.9544, 3.21995, 4.41325), (1.99, 3.26, 4.48), (1.9412, 3.2051, 4.3885) are the critical values of Elliott-Rothenberg-Stock test at (1%, 5%, 10%) significance levels for DREEXP and DREEXC, DLIPI_DSA, DLPOIL, DLNEXCR, DLNISE100 series, respectively. Asymptotic critical values of Ng-Perron test for test equations with intercept are -13.8, -8.1 and -5.7 for Mza statistics; -2.58, -1.98, -1.62 for MZt statistics; 0.174, 0.233, 0.275 for MSB statistics; and 1.78, 3.17 and 4.45 for MPT statistics at 1%, 5% and 10% significance levels, respectively. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%. [1]Series is deseasonalized using seasonal dummies.

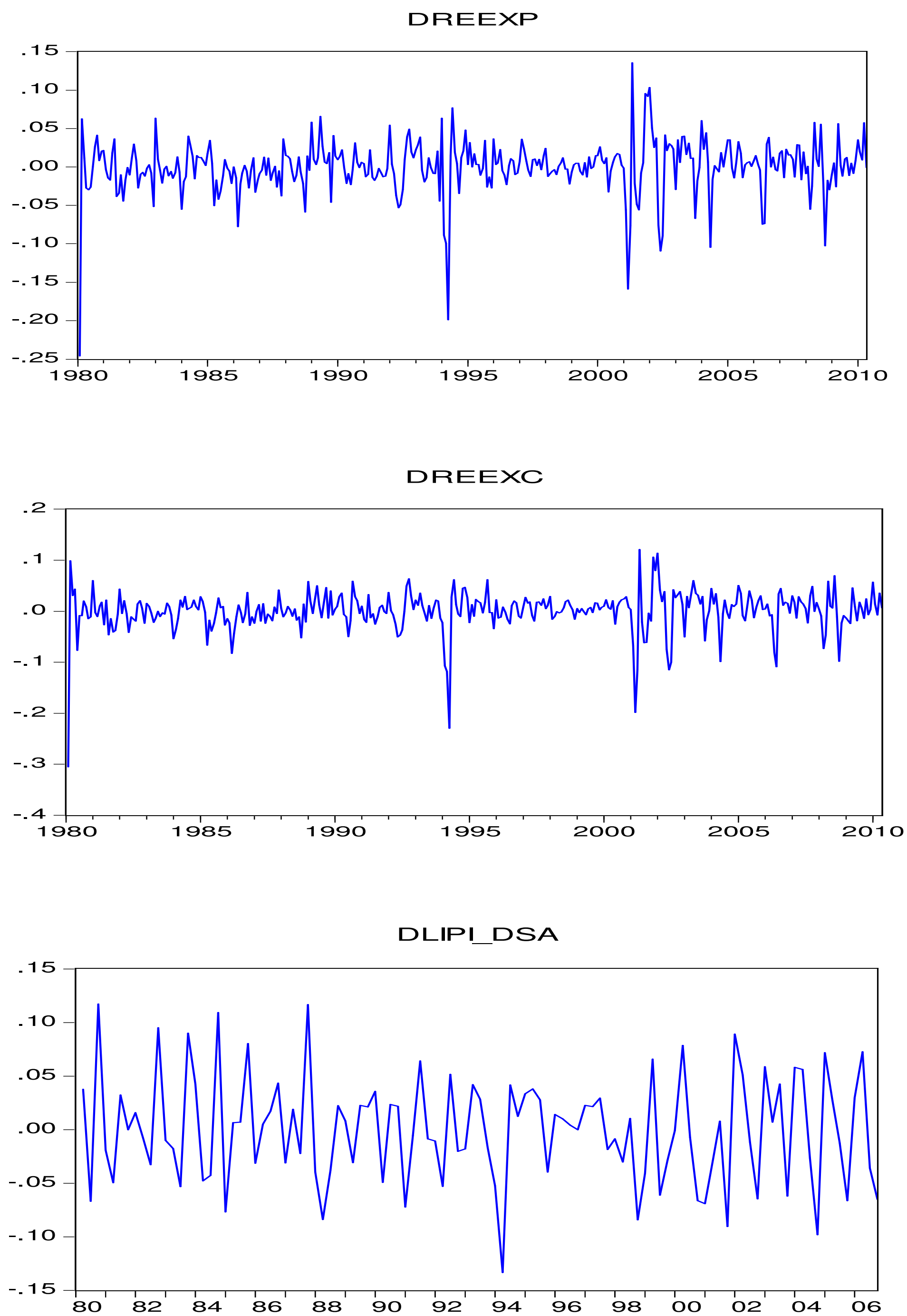


Figure 5.3 Real Exchange Rate and Industrial Production Indices Series in Logarithmic Differences

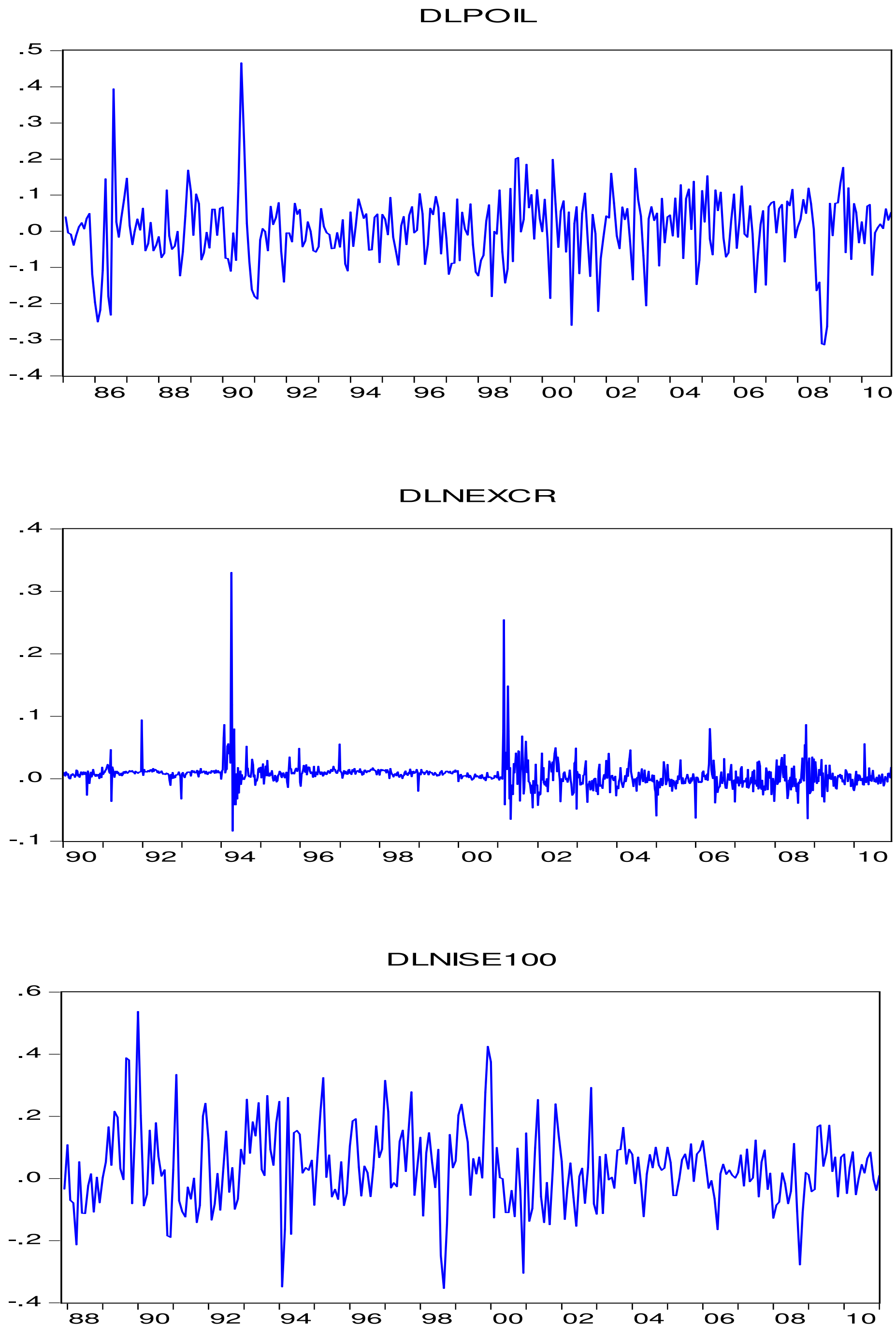


Figure 5.4 Crude Oil Spot Price, Nominal Exchange Rate and ISE 100 Index Series in Logarithmic Differences

5.2.2. Estimation Results

In the first step of ARCH modeling, an adequate conditional mean equation of the series is specified assuming constant variance. For this purpose, we employ ARMA (p, q) models. Model selection is based on Box-Jenkins (1970, 1976) methodology and besides, we follow general to specific modeling approach. First, we examine the time plot, ACF and PACF of the series and try to identify a model according to the theoretical ACF and PACF. Also, in the stage of identification, outliers, structural breaks and seasonality can be detected from these plots. To get rid of seasonality and effects of 1986 oil price collapse; 1989 stagflation; Gulf crisis between 1990 and 1991; 1994, 2001 and 2008 crises; we put seasonal dummies except for deseasonalized series and a dummy variable that takes the value of 1 in the respective month or quarter and zero, otherwise into the models. In the second stage, various models are estimated. The stationarity and invertibility of the ARMA models are checked. In the third stage, serial correlation and ARCH effect in the residuals of the models are tested. The models that pass the diagnostic test for serial correlation are compared according to Goodness of Fit criteria (AIC, SIC and HQ), forecasting performance (RMSE, MAE, MAPE and TIC) and also considering parsimony principle. Comparisons are given in Tables from 5.4 to 5.9.

Based on goodness of fit criteria, forecasting performance and parsimony principle, ARMA(1,0)(1,0), ARMA((1,2),1)(1,1), ARMA(1,1)(1,1), MA(1), ARMA(1,2), ARMA((1,12),(1,12)) models are selected for DREEXP, DREEXC, DLIPI_DSA, DLPOIL, DLNEXCR and DLNISE100 series, respectively. Results of estimation and diagnostic tests are given in Table 5.10. All the models perform well. Estimated parameters are significant. Lagged AR coefficients add up to 0.039 for DREEXP and 0.869, 0.932, 0.926 and -0.79691 indicating high level of persistence for DREEXC, DLIPI_DSA, DLNEXCR and DLNISE100 series, respectively. Ljung-Box Q-statistics of residuals do not indicate any serial correlation at various lags up to 36.

Table 5.4 Model Comparison for DREEXP series

	ARMA((1), (1, 2)) (1, 1)	ARMA(1,0) (1,0)	ARMA(12, 1)	ARMA(0,1) (0,1)	ARMA(1, 12)
Goodness of Fit					
AIC	-4.463166	-4.459833	-4.431081	-4.429951	-4.433922
SIC	-4.188182	-4.217846	-4.200093	-4.198964	-4.202935
HQ	-4.353724	-4.363524	-4.339149	-4.338020	-4.341991
Forecasting performance					
RMSE	0.032607	0.031820	0.031812	0.031630	0.031656
MAE	0.024581	0.024101	0.024016	0.023984	0.024020
MAPE	257.2001	231.6750	229.8606	237.6581	239.0809
TIC	0.822231	0.816574	0.813986	0.808868	0.808558

Notes: AIC: Akaike Information Criterion, SIC: Schwartz Information Criterion, HQ: Hannan-Quinn Information Criterion; RMSE: root mean squared error; MAE: mean absolute error; MAPE: mean absolute percentage error; TIC: Theil's Inequality coefficient. Sample is restricted for the period 1981:3-2010:5 for each estimation. Model is reestimated for the sample up to 2007:1 and dynamic forecast is performed for the period between 2007:2 and 2010:5.

Table 5.5 Model Comparison for DREEXC series

	ARMA((1,2), (1))(1, 1)	ARMA((1,2), (12))	ARMA((1, 2), 1))(0,1)
Goodness of Fit			
AIC	-4.499206	-4.384929	-4.389808
SIC	-4.201594	-4.109362	-4.103219
HQ	-4.380746	-4.275244	-4.275736
Forecasting performance			
RMSE	0.033566	0.033261	0.033332
MAE	0.024155	0.025095	0.025325
MAPE	182.6299	159.5282	163.7079
TIC	0.743776	0.818515	0.824325

Notes: Sample is restricted for the period 1981:4-2010:5 for each estimation. Model is reestimated for the sample up to 2007:1 and dynamic forecast is performed for the period between 2007:2 and 2010:5.

Table 5.6 Model Comparison for DLIPI_DSA series

	ARMA((1,2,3),(3))(1, 1)	ARMA((1,2),(4))(1,0)	ARMA(1,4)(1,0)	ARMA((1,1))(1,1)
Goodness of Fit				
AIC	-3.892856	-3.758270	-3.765573	-3.887343
SIC	-3.528132	-3.466292	-3.505056	-3.574723
HQ	-3.745246	-3.640208	-3.660137	-3.760820
Forecasting performance				
RMSE	0.032548	0.029289	0.031332	0.029258
MAE	0.026301	0.025319	0.027844	0.024155
MAPE	237.9531	252.2774	287.1590	208.7638
TIC	0.269736	0.242427	0.250982	0.246048

Notes: Sample is restricted for the period 1982Q1-2006Q4 for each estimation. Model is reestimated for the sample up to 2002Q4 and dynamic forecast is performed for the period between 2003Q1 and 2006Q4.

Table 5.7 Model Comparison for DLPOIL series

	AR(1)	MA(1)
Goodness of Fit		
AIC	-2.008476	-2.010936
SIC	-1.803567	-1.806028
HQ	-1.926562	-1.929023
Forecasting performance		
RMSE	0.108917	0.109072
MAE	0.083530	0.083413
MAPE	123.1418	123.4474
TIC	0.845267	0.841643

Notes: Sample is restricted for the period 1985:1-2010:12 for each estimation. Model is reestimated for the sample up to 2007:1 and dynamic forecast is performed for the period between 2007:2 and 2010:12.

Table 5.8 Model Comparison for DLNEXCR series

	AR(1, 2, 3, 4, 13, 14, 15)	ARMA(2, 1)	ARMA(1, 2)
Goodness of Fit			
AIC	-5.588047	-5.585048	-5.585498
SIC	-5.278351	-5.293842	-5.294292
HQ	-5.470771	-5.474773	-5.475224
Forecasting performance			
RMSE	0.018026	0.017943	0.017955
MAE	0.013881	0.013797	0.013806
MAPE	372.8606	354.8077	355.5385
TIC	0.742863	0.744184	0.744266

Notes: Sample is restricted for the period 1990W17-2010W50 for each estimation. Model is reestimated for the sample up to 2006W52 and dynamic forecast is performed for the period between 2007W1 and 2010W50.

Table 5.9 Model Comparison for DLNISE100 series

	ARMA((1,12), (1,12))	AR(1)	MA(1)
Goodness of Fit Criteria			
AIC	-1.502225	-1.455393	-1.460708
SIC	-1.219317	-1.212901	-1.218216
HQ	-1.388569	-1.357974	-1.363290
Forecasting performance Criteria			
RMSE	0.955220	0.095986	0.095902
MAE	0.072896	0.072922	0.072762
MAPE	235.9474	479.1872	478.1993
TIC	0.697773	0.701577	0.700070

Notes: Sample is restricted for the period 1988:12-2011:01 for each estimation. Model is reestimated for the sample up to 2006:12 and dynamic forecast is performed for the period between 2007:01 and 2011:01.

Table 5.10 Model Estimation and Diagnostic Tests Results

AR/MA terms	DREEXP	DREEXC	DLIPI_DSA	DLPOIL	DLNEXCR	DLNISE100
AR(1)	0.295 (0.0000)	0.918323 (0.0000)	0.41820 (0.0001)		0.926062 (0.00)	-0.338 (0.00)
AR(2)		-0.334776 (0.0000)				
AR(12)						-0.343 (0.00)
SAR(4)			0.8832 (0.0000)			
SAR(12)	-0.197 (0.0002)	0.684762 (0.0000)				
MA(1)		-0.578752 (0.0012)	-0.9787 (0.0000)	0.217831 (0.0002)	-0.696018 (0.0000)	0.6202 (0.00)
MA(2)					-0.099109 (0.0050)	
MA(12)						0.4078 (0.00)
SMA(4)			-0.6104 (0.0000)			
SMA(12)		-0.945952 (0.0000)				
L.L.[5]	804.701	814.361	198.509	329.9776	3119.447	220.7959
AIC	-4.459833	-4.499206	-3.6963	-2.012718	-5.597888	-1.502225
SIC	-4.217846	-4.201594	-3.4389	-1.808292	-5.309671	-1.219317
Diagnostic Tests						
Q(6)[1]	4.7817 (0.310)	1.3197 (0.251)	0.9422 (0.624)	6.4668 (0.263)	1.3534 (0.716)	4.4772 (0.107)
Q(12)[1]	8.4012 (0.590)	4.3281 (0.741)	4.6225 (0.797)	15.485 (0.161)	3.3909 (0.947)	10.966 (0.204)
Q(24)[1]	23.438 (0.377)	12.579 (0.859)	21.404 (0.374)	36.389 (0.038)	25.709 (0.218)	25.722 (0.175)
Q(36)[1]	30.118 (0.658)	19.291 (0.950)	26.666 (0.733)	49.919 (0.049)	39.296 (0.209)	31.615 (0.486)
$Q^2(6)$[2]	13.324 (0.010)	17.547 (0.000)	2.1446 (0.342)	15.253 (0.009)	104.21 (0.000)	11.600 (0.003)
$Q^2(12)$[2]	15.815 (0.105)	30.994 (0.000)	6.4469 (0.597)	25.331 (0.008)	129.90 (0.000)	23.036 (0.003)
$Q^2(24)$[2]	42.798 (0.005)	64.360 (0.000)	22.336 (0.323)	39.363 (0.018)	220.26 (0.000)	57.689 (0.000)

Table 5.10 (Continued)

Diagnostic Tests						
	DREEXP	**DREEXC**	**DLIPI_DSA**	**DLPOIL**	**DLNEXCR**	**DLNISE100**
$Q^2(36)^2$	51.451 (0.028)	74.467 (0.000)	43.431 (0.086)	43.755 (0.147)	231.77 (0.000)	73.189 (0.000)
$ARCH(1)^3$	5.972 (0.015)	9.033 (0.003)	0.068 (0.794)	6.027 (0.014)	60.136 (0.000)	8.841 (0.003)
$ARCH(2)^3$	7.039 (0.029)	11.304 (0.004)	0.256 (0.879)	5.989 (0.050)	63.752 (0.000)	9.604 (0.008)
$ARCH(4)^3$	7.272 (0.122)	11.648 (0.020)	1.431 (0.839)	11.093 (0.026)	66.646 (0.000)	9.425 (0.051)
$ARCH(6)^3$	11.342 (0.078)	15.693 (0.016)	2.052 (0.915)	12.635 (0.049)	75.514 (0.000)	10.121 (0.119)
$ARCH(12)^3$	13.236 (0.352)	25.751 (0.012)	6.360 (0.897)	22.135 (0.036)	82.947 (0.000)	20.301 (0.062)
$ARCH(52)^3$	-	-	-	-	123.596 (0.000)	-
Skewness	-0.2095	-0.3982	-0.4767	-0.318399	0.462743	0.25320
Kurtosis	4.8737	3.8719	3.257	3.449578	9.365419	3.22942
JB test[4]	53.913 (0.000)	20.337 (0.000)	4.144 (0.126)	7.874 (0.020)	1882.6 (0.000)	3.426 (0.180)

Notes: To save space, estimate of coefficients on constant and dummy variables are not reported. p-values are in parentheses.
[1]Ljung-Box Q-statistics of residuals for lags of 6, 12, 24, and 36 are reported to detect the evidence of serial correlation in the residuals of the models.
[2]Ljung-Box Q-statistics of squared residuals for lags of 6, 12, 24, and 36 are reported to detect the evidence of ARCH effects in the models.
[3]ARCH LM test of Engle (1982) for ARCH error is performed for 1, 2, 4, 6, 12 and 24 lags.
[4]JB test represents Jarque-Bera statistic to test normality.
[5]L.L. = Log Likelihood.

However, squared residuals show the classic volatility clustering of an ARCH process. Also ARCH-LM tests indicate the presence of ARCH effects in the residuals of the models except for DLIPI_SA series. Jarque-Bera statistic for testing normality shows departures of residuals from normality assumption in all the results of the models excluding the ones for DLIPI_DSA and DLNISE100 series. So, we can conclude that the ARMA models capture any pattern in the conditional mean of series, but does not account for the strong pattern in the conditional error variance.

After specifying our mean equation and diagnostic checking, the last step will be to estimate our ARMA (r, s)-GARCH (q, p) model from which volatility measurement will be obtained and we will modify the mean equation, accordingly. In ARCH/GARCH modeling, we consider the following issues in the model estimations and selections:

1. The estimated coefficients should be statistically significant.
2. All coefficients of conditional variance need to be positive except for EGARCH models.
3. All coefficients in both mean and variance equation need to imply convergent processes (stationarity, invertibility and finite variance properties are checked).
4. There must not be autocorrelation in the *standardized residuals* of the estimated models.
5. There must not be autocorrelation in the *squared standardized residuals* of the estimated models.
6. ARCH test for the standardized residuals need to indicate the absence of ARCH effects.
7. Leverage effects tests are performed. If test results indicate the presence of leverage effects, we need to consider this asymmetry by estimating TARCH, EGARCH, Power ARCH or asymmetric Component ARCH models.
8. Normality assumption for errors is tested. If the test indicates nonnormal errors, the model is reestimated under different assumptions on error distributions.
9. Different models are compared by using revised AIC, SIC and RSS. Maximized values of log likelihood functions are also important for the comparison of competing models.

For all the series, ARCH test indicates the presence of ARCH effects. In order to determine the order of the effect, the test is performed at various lag lengths. We estimate the largest order of ARCH model that the econometric package program allows us. In the estimation results for DREEXP, DREEXC, DLPOIL, and DLNISE100, some lags after 1 seem to be insignificant and also some of them have negative signs. Therefore, we start with ARCH(1) model. But this model cannot pass the diagnostic tests as the correlogram and ARCH tests indicate the presence of autocorrelation in the squared standardized residuals of the model (signal for remaining ARCH effects). For DLNEXCR series, the estimation of largest order ARCH model show that some lags after 2 are insignificant and also some of them have negative signs. Therefore, we start with ARCH(2) model. But this model does not have a finite variance. For ARCH(1) model, we encounter with the same problems as in the ARCH(1) model estimations for other series. Therefore, for all the series under different assumptions on error distribution, GARCH(1,1), GARCH(1,2), GARCH(2, 1) and GARCH(2, 2) models and asymmetric models such as TARCH, EGARCH, Power ARCH or asymmetric Component ARCH are estimated. In all model estimations, the log-likelihood function is maximized by Marquardt optimization algorithm. In some models, assumption of conditional normality cannot be maintained, we try t distribution and following Nelson (1991) Generalized Error Distribution (GED) as the conditional distribution of the errors. We performed leverage tests and if leverage test result indicates the presence of asymmetry, we repeat the estimation by considering leverage effects. In some cases, although the test result does not imply asymmetry, because of the problems in the model, we again estimate the model with asymmetric effects.

GARCH(1, 1) model with t distribution and GARCH(1, 1) model with GED satisfy all the conditions for DREEXP and DREEXC series. For DLIPI_DSA series, EGARCH(1, 1) model is the most suitable model based on nine criteria listed above. GARCH(1, 1) model with normally distributed errors and EGARCH (1, 1) model with GED perform well according to diagnostic tests for DLPOIL series, however, as the leverage effects test indicate the absence of asymmetry, GARCH (1, 1) model with normal distribution is employed to measure the volatility. Among various models for DLNEXCR series, IGARCH(1, 1) model with GED and EGARCH (1, 1) model with GED are two competing models satisfying most of the criteria mentioned before. If we compare them, although, leverage effects test indicates there is no asymmetry in the IGARCH (1, 1) model with GED, in the EGARCH model with

GED, the coefficients in mean and variance equations are all statistically significant at most 10% significance level. The model satisfies all the criteria below is the EGARCH (1, 1) model with GED; therefore this model is used to measure the volatility based on modified AIC and SIC, such that for IGARCH (1, 1) model with GED we calculate modified AIC and SIC as (-3447.543, -3117.822) and for EGARCH model with GED as (-3484.711, -3140.003). And also, in Turkey between the years considered in the analysis, different exchange rate regimes are implemented. Using a model considers asymmetric effects will be more suitable in this context. For DLNISE100 series, again we have two models perform well: IGARCH(1, 1) model with normally distributed errors and EGARCH (1, 2) model with normal distribution assumption. Leverage effects test indicates there is some asymmetry in the IGARCH (1, 1) model at 0.01 significance level. In the EGARCH model, the coefficients in mean and variance equations are all statistically significant at most 10% significance level. The model satisfies all the criteria above is the EGARCH (1, 2) model; therefore this model is used to measure the volatility based on the comparison between two model's modified AIC and SIC as (-171.843, -100.173) for IGARCH(1, 1) model and (-192.966, -106.962) for EGARCH model. Results of estimations and diagnostic tests for the selected models are presented in Table 5.11.

Ljung-Box statistics of the standardized and the squared standardized residuals for model of each series indicates that there is no evidence of autocorrelation in standardized and the squared standardized residuals. ARCH-LM test for the standardized residuals support the result obtained by checking autocorrelation in squared standardized residuals that there is no remaining GARCH effects in the models.

Table 5.11 (G)ARCH Model Estimation and Diagnostic Tests Results

AR/MA terms	DREEXP	DREEXC	DLIPI_DSA	DLPOIL	DLNEXCR	DLNISE100
CONDITIONAL MEAN EQUATION						
AR(1)	0.230113 (0.0001)				0.993616 (0.0000)	
AR(2)			0.598382 (0.0000)			
AR(12)		0.125547 (0.0216)				-0.875395 (0.0000)
SAR(4)			0.916468 (0.0000)			
SAR(12)	-0.122031 (0.0018)					
MA(1)		0.300046 (0.0000)	-0.172331 (0.0000)	0.171013 (0.0073)	-0.752584 (0.0000)	0.074298 (0.0036)
MA(2)			-0.800682 (0.0000)		-0.106047 (0.0000)	
MA(12)						0.896482 (0.0000)
SMA(4)			-0.619995 (0.0000)			
SMA(12)		-0.235231 (0.0006)				
(LOGARITHM OF) CONDITIONAL VARIANCE EQUATION ((ln)h_t)[1]						
ε_{t-1}^2	0.448902 (0.0225)	0.073846 (0.0479)		0.232340 (0.0013)		
h_{t-1}	0.540496 (0.0000)	0.891018 (0.0000)		0.650589 (0.0000)		
$\varepsilon_{t-1}/h_{t-1}^{0.5}$			-0.375057 (0.0016)		0.056596 (0.0982)	-0.047712 (0.0027)
$\lvert\varepsilon_{t-1}/h_{t-1}^{0.5}\rvert$			-1.169904 (0.0000)		0.394638 (0.0000)	0.465468 (0.0002)
ln(h_{t-1})			0.497562 (0.0000)		0.961388 (0.0000)	0.058192 (0.0889)
ln(h_{t-2})						0.921956 (0.0000)
t-dist. dof	3.305008 (0.0001)					
GED Parameter		1.082459 (0.0000)			0.799967 (0.0000)	

Table 5.11 (Continued)

	DREEXP	DREEXC	DLIPI_DSA	DLPOIL	DLNEXCR	DLNISE100
L.L.[2]	810.120	825.7731	201.9997	325.973	3622.711	240.9664
AIC[3]	-770.12	-767.773	-178	-311.973	-3484.71	-192.966
SIC[4]	-692.90	-655.728	-146.618	-285.794	-3140	-106.962
DIAGNOSTIC TESTS						
Q(6)[5]	4.6663 (0.323)	7.1750 (0.067)	2.7679 (0.096)	6.9779 (0.222)	2.7148 (0.438)	5.1779 (0.159)
Q(12)[5]	6.4511 (0.776)	10.109 (0.342)	5.7937 (0.564)	16.164 (0.135)	7.2410 (0.612)	13.770 (0.131)
Q(24)[5]	16.304 (0.801)	16.742 (0.727)	22.298 (0.270)	36.859 (0.034)	28.582 (0.124)	24.084 (0.289)
Q(36)[5]	29.068 (0.708)	22.855 (0.907)	31.325 (0.450)	49.114 (0.057)	33.994 (0.420)	37.427 (0.273)
$Q^2(6)$[6]	2.0240 (0.731)	3.2774 (0.351)	2.4267 (0.119)	5.6800 (0.339)	1.7194 (0.633)	6.7418 (0.081)
$Q^2(12)$[6]	6.3104 (0.789)	16.756 (0.053)	5.4628 (0.604)	16.162 (0.135)	3.3966 (0.946)	10.877 (0.284)
$Q^2(24)$[6]	24.372 (0.328)	30.693 (0.079)	13.880 (0.791)	34.676 (0.056)	5.9430 (0.999)	25.697 (0.218)
$Q^2(36)$[6]	31.215 (0.605)	35.763 (0.340)	21.101 (0.909)	47.137 (0.083)	8.7375 (1.000)	33.757 (0.431)
ARCH(1)[7]	0.207 (0.649)	0.132 (0.716)	0.165 (0.685)	0.019 (0.890)	0.000 (0.993)	1.506 (0.219)
ARCH(2)[7]	0.476 (0.788)	0.285 (0.867)	0.342 (0.843)	0.626 (0.731)	0.232 (0.890)	2.522 (0.283)
ARCH(4)[7]	1.849 (0.764)	1.282 (0.864)	2.389 (0.665)	1.653 (0.799)	0.795 (0.939)	6.058 (0.195)
ARCH(6)[7]	2.232 (0.898)	3.056 (0.802)	2.312 (0.889)	5.947 (0.429)	1.768 (0.940)	6.227 (0.398)
ARCH(12)[7]	7.347 (0.834)	15.196 (0.231)	5.281 (0.948)	15.507 (0.215)	3.471 (0.991)	10.194 (0.599)
ARCH(52)[7]	-	-	-	-	11.903 (1.000)	-

Table 5.11 (Continued)

	DREEXP	DREEXC	DLIPI_DSA	DLPOIL	DLNEXCR	DLNISE100
Skewness	-0.452759	-0.521381	-0.328273	-0.314116	1.793850	0.011742
Kurtosis	5.396742	5.075700	2.950175	3.056065	27.12132	3.258332
JB test[8]	96.003 (0.000)	79.139 (0.000)	1.825 (0.402)	5.155 (0.076)	27059.2 (0.000)	0.746 (0.689)
Leverage Effects Test[9]	1.835 (0.042)	1.263 (0.239)	0.399 (0.959)	0.529 (0.895)	0.742 (0.913)	0.102 (0.749)

Notes: To save space, estimate of coefficients on constant and dummy variables are not reported. p-values are in parentheses.
[1]For EGARCH models, estimation results are for logarithm of conditional variance; [2]L.L. = Log Likelihood, [3]Akaike Information criterion is calculated by the following formula: AIC=-lnL+2n where n are the number of the estimated parameters and lnL is the Log Likelihood; [4]Schwartz Bayesian criterion is calculated by the following formula: SIC=-lnL+n*ln(T) where T is the number of observation, n and lnL is as defined above; [5]Ljung-Box Q-statistics of residuals for lags of 6, 12, 24, and 36 are reported to detect the evidence of serial correlation in the standardized residuals of the models; [6]Ljung-Box Q-statistics of squared standardized residuals for lags of 6, 12, 24, and 36 are reported to detect the evidence of ARCH effects in the models; [7]ARCH LM test of Engle (1982) for ARCH error is performed for 1, 2, 4, 6, 12 and 24 lags;[8]JB test represents Jarque-Bera statistic to test normality; [9]Leverage effects test is performed after estimating the symmetric models. To test the leverage effect following regression is estimated;

$$s_t^{\,2} = a_0 + \sum_{i=1}^{n} a_i s_{t-i}$$

where s_t is the standardized residuals $\left[s_t = \frac{\hat{\varepsilon}_t}{\hat{h}_t^{1/2}} \right]$ obtained from symmetric models. In this regression, joint significance of a_i coefficients is tested by F test. Joint significance indicates that there are leverage effects.

In asymmetric models for DLIPI_SA, DLNEXCR and DLNISE100 series, there are significant leverage effects as we have significant asymmetry coefficients on $\varepsilon_{t-1}/h_{t-1}^{0.5}$ variable in conditional variance equations. In the model for DLNEXCR, the asymmetry coefficient is positive implying that unanticipated increase in nominal exchange rate growth (one-unit increase) increases logarithm of the conditional variance (by 0.451234 unit) more than the unanticipated decrease in nominal exchange rate growth (one unit decrease) (increase by 0.338042) as coefficient on $\left|\varepsilon_{t-1}/h_{t-1}^{0.5}\right|$ is positive. In model for DLIPI_DSA, given the value of σ_{t-1}, a one-unit decline in ε_{t-1} will cause 0.79485 units decrease in the logarithm of the conditional variance; however, a one-unit increase in ε_{t-1} will cause 1.54496 units decline in the logarithm of the conditional variance. For model of DLNISE100 series, asymmetry coefficient is negative; in this case, unanticipated decrease in nominal exchange rate growth increases logarithm of the conditional variance more than the unanticipated increase in nominal exchange rate growth, as coefficient on $|\varepsilon_{t-1}/h_{t-1}^{0.5}|$ is positive such that one unit decrease and increase in ε_{t-1} lead 0.51318 and 0.417756 units increases, respectively. We also test if positive and negative shocks have significant impacts on $\ln h_t$. Following F statistics with associated p-values are obtained for DLIPI_SA, DLNEXCR and DLNISE100 series for significance test of positive (negative) shocks, respectively, 84.24760 [0.0000] (13.10061 [0.0005]), 54.96180 [0.0000] (23.95695 [0.0000]) and 14.53755 [0.0002] (13.67218 [0.0003]) showing the significant effect of both negative and positive shocks.

In all the models, there is significant seasonality in the conditional means and non-explosion conditions for conditional mean (sums of AR coefficients are less than one) and (log)conditional variance are satisfied; but in models for DREEXP, DREEXC and DLPOIL series, sums of coefficients on ε_{t-1}^2 and h_{t-1}; for DLNEXCR series, coefficient on $\ln(h_{t-1})$ and for DLNISE100 series, sums of coefficients on $\ln(h_{t-1})$ and $\ln(h_{t-2})$ are very close to 1 implying high persistence in the conditional variance. So, in all the models, (log of) conditional variance is strictly stationary and ergodic. To have finite unconditional moments and thus covariance stationarity for ε_t and σ_t^2, we also have condition on the shape parameter of the GED. Shape parameter shows the tail-thickness. The GED with shape parameter=2 is a normal distribution; with shape parameter<2 (>2), we have fat-tailed (thin-tailed) distribution compared to normal distribution; and when shape parameter=1, distribution is double exponential. If shape parameter tends to ∞, variable of interest is uniformly distributed over the interval $[-3^{1/2}, 3^{1/2}]$. For covariance stationarity, we need shape parameter>1 implying thinner tailed distribution than the double exponential distribution. In model for DLNEXCR series, this condition is not satisfied as shape parameter is smaller than one, implying significant fatter tails than the double exponential distribution.[1]

From these ARCH/GARCH model estimations, we obtain conditional variances of growth of real exchange rate calculated using PPI, growth of real exchange rate calculated using CPI, industrial production index growth, crude oil price growth, nominal exchange rate growth and İstanbul Stock Exchange-100 index growth. In sections 7 for the panel data application of Turkey, the quarterly, monthly and weekly averages of conditional variances are used as a proxy for annual economic volatility. In section 8 for the panel data application of OECD countries, we employ only the monthly averages of conditional variance associated with oil price variable.

5.2.3. Volatility Measures and Comparison of Volatilities

This section presents the volatility measures to be employed in panel data applications for Turkey and OECD countries. Figure 5.5, 5.6, 5.7, and 5.8 illustrate the exchange rate, industrial production, oil price, and stock market volatilities calculated between 1990 and 2001 to be employed for the application on Turkey and Figure 5.9 shows the oil price volatility calculated between 1985 and 2007 to be employed for the application on OECD countries.

We can compare the exchange rate, industrial production, oil price, and stock market volatilities calculated between 1990 and 2001 to be employed for the panel application on the provinces of Turkey. Figure 5.5 demonstrates that each volatility measure can capture different economic events, more clearly. Although in 2001, most of the volatilities rapidly increase as a result of economic crisis in Turkey, we observe that industrial production, stock market and nominal exchange rate volatility series reach their highest values reflecting the period of high uncertainty. Other economic crises such as 1994 crisis seem to be better reflected in the volatility

[1] For the detailed information on the non-explosion conditions for EGARCH models, see Nelson (1991).

measures based on real and nominal exchange rates. Besides, increase in stock market volatility for year 1991 can be due to Gulf crisis between 1990 and 1991. Lastly, Henriques and Sadorsky (2011) have explained the source of the sharp increases in oil price volatility in 1999 and 2001 as the concerns about year 2000 problem (millennium bug) in 1999 and September 11, 2001 Terrorist attack on World Trade Centre in New York.

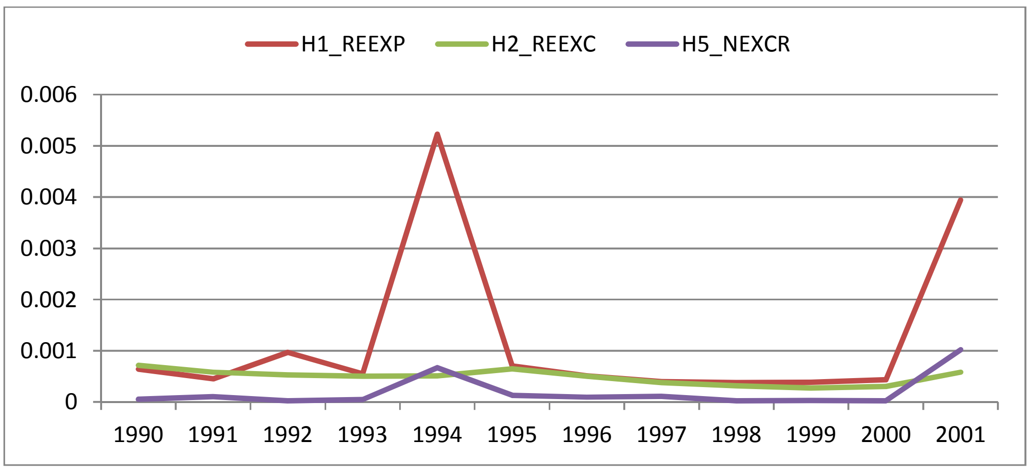


Figure 5.5 Real Exchange Rate and Nominal Exchange Rate Volatility Series, 1990-2001

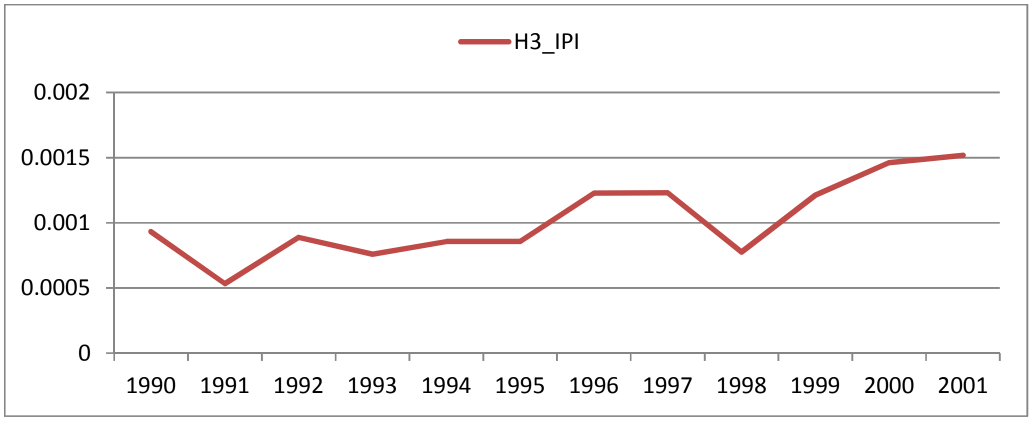


Figure 5.6 Industrial Production Volatility Series, 1990-2001

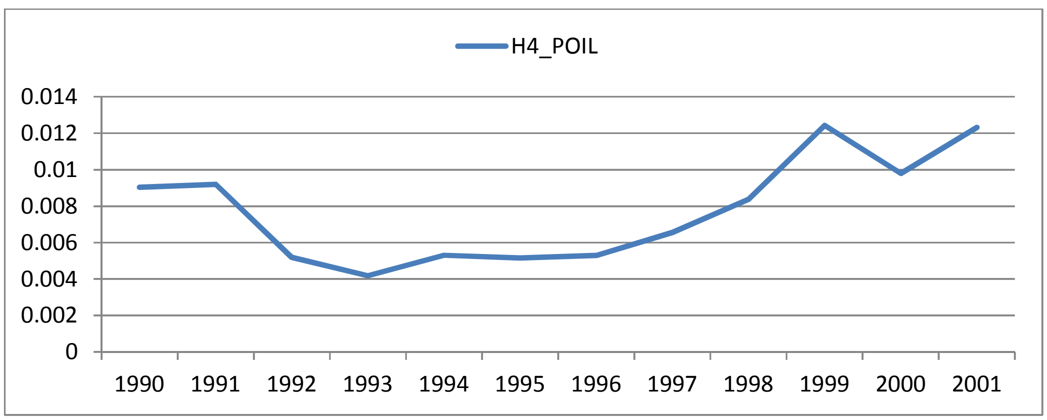


Figure 5.7 Oil Price Volatility Series, 1990-2001

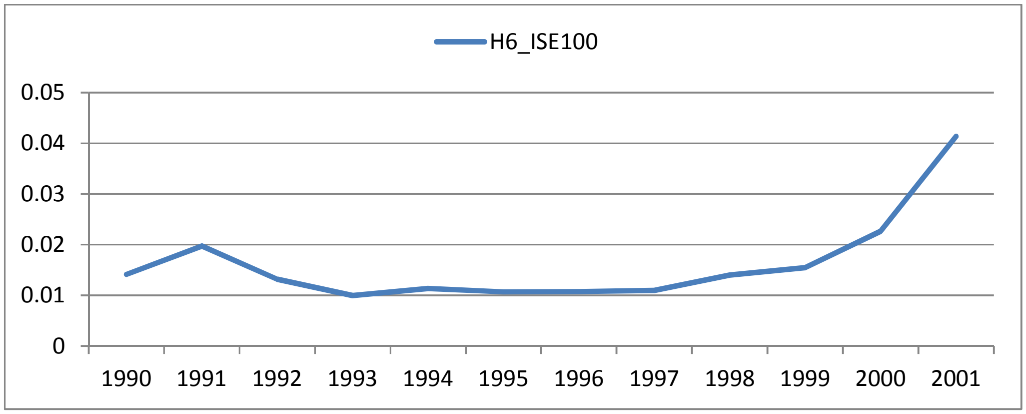


Figure 5.8 Stock Market Volatility Series, 1990-2001

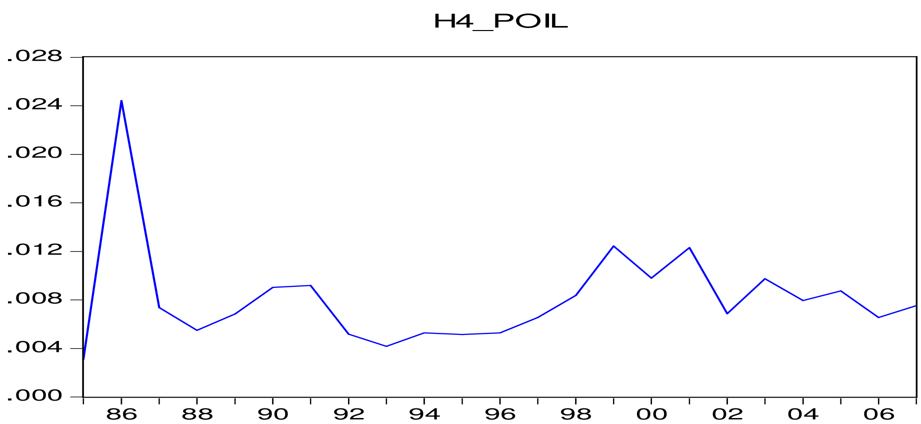


Figure 5.9 Oil Price Volatility Series, 1985-2007

CHAPTER 6

PANEL DATA METHODS

In this section, we discuss the panel data methods and models that we employ in sections 7 and 8 such as pooled model, fixed effects model, dynamic panel data model, panel unit root and cointegration tests, panel cointegration model, panel error correction model and estimation methods for each model. According to Chakir et al. (2003), biased estimates for coefficients can be resulted from time series and cross section studies as they do not control for individual heterogeneity, however, in panel data, one can consider individual heterogeneity. Therefore, in this study, we employ panel data techniques.

A panel data set contains repeated observations over the same units collected over a number of periods (Verbeek, 2004: 341). Panel data has many advantages. According to Hsiao (2007) and Baltagi (2008), advantages of panel data over one-dimensional data are variation increase in the data; efficiency improvement in the estimates; more precise predictions; ability to consider and make inferences on the complicated behavioral hypothesis; reduction in aggregation biases; simplification in the estimation and statistical inferences; ability to handle with unobserved or missing variables, unrestricted dynamic relations, heterogeneity in the data, measurement errors and nonstationary time series. On the other hand, there are some disadvantages of panel data listed by Baltagi (2008) such as problems of data collection, measurement errors, cross-sectional dependence and limited time series dimension. Besides these disadvantages, as using panel data provide many benefits that are mentioned above, there are huge amount of theoretical and empirical contributions in this area. However, in our study, we restrict our attention on balanced panel data, single-equation one-way linear panel data models and estimation methods of least squares, instrumental variables and GMM. In section 6.1, we discuss various models and associated estimation methods that we employ in our empirical study in sections 7 and 8. We give brief information on panel unit root and panel cointegration tests in section 6.2.

6.1. Models, Estimation Methods and Diagnostic Tests

We start with pooled model assuming that all the coefficients in the model are same across cross-sectional units and time series observations in section 6.1.1. Then, in section 6.1.2, we relax this assumption and allow for some heterogeneity. 6.1.3 discusses the diagnostic tests for pooled and fixed effects model. Section 6.1.4 further extends the model with the inclusion of dynamics by using a lagged dependent variable as a regressor. If we ignore the nonstationarity of variables in fixed effects model, we face spurious regression problem. Therefore, section 6.1.5 provides information on panel cointegration model and its estimation. In our empirical study, to distinguish short run and long run dynamics, we build a panel error correction model and in section 6.1.6, we discuss the estimation of panel error correction model.

6.1.1. Estimation of Pooled Model

We assume that we have a panel data of N cross section units over T observations and k+1 exogenous explanatory variables including the intercept term denoted by $X_{i,t,j}$ for i=1,..,N; t=1,...,T and j=1,..,k. In the pooled model, all the coefficients are assumed to be same over time and cross-sections. Therefore, pooled model can be shown by the following expression for each i and t;

$$y_{i,t} = \alpha + \beta_1 X_{i,t,1} + \beta_2 X_{i,t,2} + \cdots + \beta_k X_{i,t,k} + \varepsilon_{i,t} \tag{6.1}$$

where, $\varepsilon_{i,t} \sim iid\ N(0,\sigma^2)\ for\ all\ i\ and\ t.$ $X_{i,t,j}$ ‘s are assumed to be uncorrelated with $\varepsilon_{i,t}$. OLS method can be employed to estimate this model. However, if we ignore the heterogeneity (for example, individual fixed effects) in the data although it exists, this leads omitted variable bias causing pooled OLS estimator to be biased and inconsistent (Baltagi, 2008: 15).

6.1.2. Estimation of Fixed Effects Model

We concentrate only on one-way fixed effects model which allows the intercept term to vary across cross-sections as our model contains cross-section invariant variable, namely volatility variable and because, cross-sectional units of data sets in our applications are formed according to predefined groups, we assume that effects if exists are fixed as suggested by Erlat (2011) and Judson and Owen (1996). But if cross-sectional units were selected based on random sampling procedure, then assumption of random effects will be more appropriate. The equation for fixed effects model is given below;

$$y_{i,t} = \alpha_i + \beta_1 X_{i,t,1} + \beta_2 X_{i,t,2} + \cdots + \beta_k X_{i,t,k} + \varepsilon_{i,t} \tag{6.2}$$

where $\varepsilon_{i,t} \sim iid\,(0, \sigma^2)$ $for\ all\ i\ and\ t.$ Here, α_i represents the observed and unobserved effects fixed over time and may potentially be correlated with Xitj's. Instead of defining a dummy variable for each i and inserting them into the model, we use within transformation of the data to eliminate the fixed effects.

$$y_{i,t} - \bar{y}_i = \beta_1(X_{i,t,1} - \bar{X}_{i,1}) + \beta_2(X_{i,t,2} - \bar{X}_{i,2}) + \cdots + \beta_k(X_{i,t,k} - \bar{X}_{i,k}) + (\varepsilon_{i,t} - \bar{\varepsilon}_i) \tag{6.3}$$

where, $\bar{y}_i = T^{-1}(\sum_{t=1}^{T} y_{i,t})$; $\bar{X}_{i,j} = T^{-1}(\sum_{t=1}^{T} X_{i,t,j})$; $\bar{\varepsilon}_i = T^{-1}(\sum_{t=1}^{T} \varepsilon_{i,t})$.

By applying OLS to the within transformed data, we can obtain unbiased within estimator as follows assuming $X_{i,t,j}$'s are strictly exogenous (Verbeek, 2004: 346);

$$\hat{\beta}_{FE} = \begin{pmatrix} \hat{\beta}_{1,FE} \\ \hat{\beta}_{2,FE} \\ \vdots \\ \hat{\beta}_{k,FE} \end{pmatrix} = \left(\sum_i \sum_t (x_{i,t} - \bar{x}_i)\,(x_{i,t} - \bar{x}_i)'\right)^{-1} \left(\sum_i \sum_t (x_{i,t} - \bar{x}_i)\,(y_{i,t} - \bar{y}_i)\right)$$

(6.4)

$$\hat{\alpha}_i = \bar{y}_i - \bar{x}_i{}'\hat{\beta}_{FE} \tag{6.5}$$

Here, $x_{i,t} = \begin{pmatrix} X_{i,t,1} \\ X_{i,t,2} \\ \vdots \\ X_{i,t,k} \end{pmatrix}$ $and\ \bar{x}_i = \begin{pmatrix} \bar{X}_{i,1} \\ \bar{X}_{i,2} \\ \vdots \\ \bar{X}_{i,k} \end{pmatrix}$

The covariance matrix of $\hat{\beta}_{FE}$ is $cov(\hat{\beta}_{FE}) = \sigma_\varepsilon^2 \left(\sum_i \sum_t (x_{i,t} - \bar{x}_i)\,(x_{i,t} - \bar{x}_i)'\right)^{-1}$ where $\sigma_\varepsilon^2 = [N(T-1)]^{-1} SSR_W$. SSR_W is the within residual sum of squares.

6.1.3. Diagnostic Tests for Pooled and Fixed Effects Model

In this section, we explain diagnostic tests for pooled and fixed effects models, very briefly.

6.1.3.1. Test for the Presence of Fixed Effects

In order to test for fixed effects, we employ following F test given by (Baltagi, 2008: 15);

$$F = \frac{(SSR_{pooled} - SSR_{lsdv})/(N-1)}{SSR_{lsdv}/(NT-N-k)} \sim F_{N-1,N(T-1)-k} \text{ under } H_0\colon \mu_1 = \cdots = \mu_{N-1} = 0$$

(6.6)

SSR denotes residual sum of squares from either pooled or Least Squares Dummy Variable (LSDV) regression. Pooled model is defined above. LSDV model is as follows;

$$y_{i,t} = \alpha + \beta_1 X_{i,t,1} + \beta_2 X_{i,t,2} + \cdots + \beta_k X_{i,t,k} + \mu_1 * D_1 + \cdots + \mu_{N-1} * D_{N-1} + +\varepsilon_{i,t} \tag{6.7}$$

$D_1, \dots, D_{N-1}$ are the dummy variables that takes value one only for 1st,...,(N-1)th cross sections, respectively and zero, elsewhere.

6.1.3.2. Autocorrelation Test

In order to test for first order autocorrelation, we assume the first order autocorrelation of the form as below;

$$\varepsilon_{i,t} = \rho\varepsilon_{i,t-1} + v_{i,t} \tag{6.8}$$

where $|\rho| < 1 \; and \; v_{i,t} \sim iid(0, \sigma_v^2)$. For both, fixed effects and pooled model, we want to test the hypothesis that $H_0: \rho = 0$. Baltagi and Li (1995) propose the following LM statistics (Baltagi, 2008: 106);

$$LM_\rho = \left({NT^2}/{(T-1)} \right) * \left(\frac{\sum_{i=1}^{N} \sum_{t=2}^{T} \tilde{\varepsilon}_{i,t} \tilde{\varepsilon}_{i,t-1}}{\sum_{i=1}^{N} \sum_{t=1}^{T} \tilde{\varepsilon}_{i,t}{}^2} \right)^2 \sim \chi_1^2 \; under \; H_0 \; for \; large \; T \tag{6.9}$$

where $\tilde{\varepsilon}_{i,t}$ are the residuals obtained from the OLS estimation of pooled model (within estimation in the case of fixed effects model) under the assumption of no autocorrelation.

Another test is developed by Wooldridge (2002). This test is based on the residuals ($\hat{e}_{i,t}$) obtained from the regression of the model transformed by first differencing.

$$\Delta y_{i,t} = \beta_1 \Delta X_{i,t,1} + \beta_2 \Delta X_{i,t,2} + \cdots + \beta_k \Delta X_{i,t,k} + \Delta\varepsilon_{i,t} \quad (6.10)$$

where we call $\Delta\varepsilon_{i,t}$ as $e_{i,t}$. We estimate this equation and obtain $\hat{e}_{i,t}$. If $\varepsilon_{i,t}$ is not serially correlated, then $corr(e_{i,t}, e_{i,t-1}) = -0.5$. To test for the first order autocorrelation in the ε_{it} , following auxiliary regression model is estimated;

$$\hat{e}_{i,t} = \rho_1 \hat{e}_{i,t-1} + error, \text{ for t=3,4,..,T and i=1,2,..,N.} \quad (6.11)$$

Here, usual t test on $\hat{\rho}$ is performed with $H_0: \rho_1 = -0.5$. In addition to the above two tests, Arellano and Bond (1991) autocorrelation test is also performed in order to test for first and second order autocorrelation. For further information on the test statistics, one can refer Arellano and Bond (1991) original paper.

6.1.3.3. Heteroscedasticity Test

In order to test for heteroscedasticity, we employ two tests: one is based on LM approach and other is LR-based test. We want to test the null hypothesis that $H_0: \sigma_{\varepsilon,i}^2 = \sigma_\varepsilon^2$ for all i = 1,2,...,N against the alternative that $H_1: \sigma_{\varepsilon,i}^2 \neq \sigma^2$ for at least one i. LM and LR test statistics are given by the following expressions (Greene, 2003: 328);

$$LM_H = \frac{T}{2} \sum_{i=1}^{N} \left(\frac{\hat{\sigma}_{\varepsilon,i}^2}{\hat{\sigma}_\varepsilon^2} - 1 \right)^2 \sim \chi_{N-1}^2 \; under \; H_0 \quad (6.12)$$

$$LR_H = T\left(ln\left|\hat{\Sigma}_{\text{homoscedastic}}\right| - ln\left|\hat{\Sigma}_{\text{heteroscedastic}}\right| \right) \quad (6.13)$$

$$= \text{NTln}\hat{\sigma}_\varepsilon^2 - \sum_{i=1}^{N} T ln\, \hat{\sigma}_{\varepsilon,i}^2 \sim \chi_{N-1}^2 \; under \; H_0$$

where, $\hat{\sigma}_{\varepsilon,i}^2 = (\sum_{t=1}^{T} \tilde{\varepsilon}_{i,t}^2 \;)/\text{T}$ and $\hat{\sigma}_\varepsilon^2 = (\sum_{i=1}^{N} \hat{\sigma}_{\varepsilon,i}^2 \;)/\text{N}$ and $\tilde{\varepsilon}_{i,t}$ are the residuals obtained from the OLS estimation of pooled model (within estimation in the case of fixed effects model).

6.1.3.4. Cross-Sectional Dependence Test

The recent literature on panel data emphasizes that there is evidence of serious cross-sectional dependence in the errors of panel data models which may be due to common shocks, unobserved components and spatial dependence (De Hoyos and Sarafidis, 2006: 482). In our empirical study, we employ three cross-sectional dependence test developed by Pesaran (2004), Friedman (1937) and Frees (1995) which are mentioned in De Hoyos and Sarafidis (2006). Equations (6.14), (6.15) and (6.16) show expressions for Pesaran (2004) CD test, Friedman (1937) FR test and Frees (1995) FREE test statistics, respectively (De Hoyos and Sarafidis, 2006:485, 486, 488);

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{i,j}\right) \sim N(0,1)\ for\ large\ T\ and\ as\ N \rightarrow \infty \qquad (6.14)$$

where, $\hat{\rho}_{i,j}$ is the sample estimate of pairwise correlation of residuals.

$$FR = (T-1)\left\{\frac{2}{N}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{r}_{i,j}\right)+1\right\} \sim \chi^2_{T-1}\ for\ fixed\ T\ and\ large\ N \qquad (6.15)$$

where, $\hat{r}_{i,j}$ is the sample estimate of the rank correlation coefficient of residuals.

$$FREE = \frac{N\left\{\left[\frac{2}{N(N-1)}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{r}_{i,j}^2\right)\right]-(T-1)^{-1}\right\}}{\sqrt{Var(Q)}} \sim N(0,1)\ for\ large\ T \qquad (6.16)$$

where, Q distribution is a joint distribution of two independent χ^2_{T-1} and $\chi^2_{T(T-3)/2}$ random variables.

Among these tests, as Frees' test is based on the sum of squared rank correlation coefficients, it is advantageous over the other two tests in the cases where the correlations alternate in sign and there is possibility of cancelling each other out causing the test cannot detect cross-sectional dependence.

6.1.4. Estimation of Dynamic Panel Data Model

In order to introduce a partial adjustment process or to get rid of autocorelation, dynamic panel data model can be employed. However, according to Bun and Kiviet (2006), although inclusion of lagged dependent variable to the model allows taking into account dynamic adjustment process, it leads to small sample bias and poor asymptotic approximation problems. We consider the following fixed effects dynamic panel data model for large N and small T panel data throughout this chapter assuming that coefficients (excluding intercept) and error variances are same across cross-sectional units;

$$y_{i,t} = \alpha_i + \delta y_{i,t-1} + \beta_1 X_{i,t,1} + \beta_2 X_{i,t,2} + \cdots + \beta_k X_{i,t,k} + \varepsilon_{i,t} \qquad (6.17)$$

We assume that errors are uncorrelated with explanatory variables, not serially correlated and are homoscedastic (Sevestre and Trognon, 1996: 123). We apply within transformation to the model as follows;

$$y_{i,t} - \bar{y}_i{}' = \delta(y_{i,t-1} - \bar{y}_{i-1}) + \beta_1(X_{i,t,1} - \bar{X}_{i,1}{}') + \beta_2(X_{i,t,2} - \bar{X}_{i,2}{}') + \cdots +$$
$$\beta_k(X_{i,t,k} - \bar{X}_{i,k}{}') + (\varepsilon_{i,t} - \bar{\varepsilon}_i{}') \qquad (6.18)$$

where, t=2,....,T and i=1,...,N; $\bar{y}_i{}' = (T-1)^{-1}(\sum_{t=2}^{T} y_{i,t})$; $\bar{y}_{i-1} = (T-1)^{-1}(\sum_{t=2}^{T} y_{i,t-1})$; $\bar{X}_{ij}{}' = (T-1)^{-1}(\sum_{t=2}^{T} X_{i,t,j})$; $\bar{\varepsilon}_i{}' = (T-1)^{-1}(\sum_{t=2}^{T} \varepsilon_{i,t})$.

Here, we can write the transformed lagged dependent variable and error term explicitly as follows to see the negative correlation between them shown by Nickell (1981) (Bond, 2002:144);

$$y_{i,t-1} - \frac{1}{T-1}(y_{i,1} + y_{i,2} + \cdots + y_{i,t} + \cdots + y_{i,T-1}) \qquad (6.19)$$
$$\varepsilon_{i,t} - \frac{1}{T-1}(\varepsilon_{i,2} + \varepsilon_{i,3} + \cdots + +\varepsilon_{i,t-1} + \cdots + \varepsilon_{i,T})$$

We can see the negative correlations between $-\frac{1}{T-1}y_{i,t}$ and $\varepsilon_{i,t}$; between $y_{i,t-1}$ and $-\frac{1}{T-1}\varepsilon_{i,t-1}$ and also positive correlations between $-\frac{1}{T-1}y_{i,t-1}$ and $-\frac{1}{T-1}\varepsilon_{i,t-1}$ such that negative correlations dominate positive correlations. "Within estimator is downward biased" (Bond, 2002:144) and inconsistent for large N and small T; however for large T, it is consistent shown by Judson and Owen (1999) (Baltagi, 2008: 147).

For this endogeneity problem, many solutions based on IV, GMM and Maximum Likelihood estimation methods are proposed. Maximum likelihood estimation of dynamic panel data models with small T is discussed by Hsiao, Pesaran and Tahmiscioglu (2002). But here, we focus only on IV and GMM estimation methods suggested by Balestra and Nerlove (1966), Anderson and Hsiao (1981, 1982), Arellano and Bond (1991), Arrelano and Bover (1995) and Blundell and Bond (1998). Below, these proposed methods are discussed, briefly.

The first attempt to solve asymptotic correlation problem in the context of within estimation is based on IV method. Balestra and Nerlove (1966) suggest to instrument $y_{i,t-1}-\bar{y}_{i-1}$ with $x_{i,t-1}-\bar{x}_{i-1}$ (Harris, Mátyás and Sevestre, 2008: 256; Sevestre and Trognon, 1996: 125). In order to get rid of fixed effects, Anderson and Hsiao (1981, 1982) employ first difference transformation.

$$\Delta y_{i,t}=\delta\Delta y_{i,t-1}+\beta_1\Delta X_{i,t,1}+\beta_2\Delta X_{i,t,2}+\cdots+\beta_k\Delta X_{i,t,k}+\Delta\varepsilon_{i,t} \qquad (6.20)$$

where, Δ denotes difference operator; $|\delta|<1,\ \Delta y_{i,t}=y_{i,t}-y_{i,t-1},\ i=1,2,\dots,N \ and\ t=3,4,\dots,T$.

OLS estimate of the above model is downward inconsistent (Bond, 2002: 145) as there is endogeneity problem such that $E(\Delta y_{i,t-1}\,\Delta\varepsilon_{i,t}) \neq 0$. Consistent estimates of coefficients can be obtained by using two stage least squares with instrumental variables that are both correlated to $\Delta y_{i,t-1}$ and orthogonal to $\Delta\varepsilon_{i,t}$ (Bond, 2002: 145).

Anderson and Hsiao (1981, 1982) propose two instrumental variables $\Delta y_{i,t-2}$ and $y_{i,t-2}$ that satisfy these two conditions. However, Arrelano (1989) shows that estimator that uses $\Delta y_{i,t-2}$ as an instrument suffers from large variance and singularity point as mentioned by Baltagi (2008). Anderson and Hsiao (1981) estimator is shown as below;

$$\widehat{\Upsilon}_{AH} = \begin{pmatrix} \widehat{\delta} \\ \hat{\beta}_1 \\ \hat{\beta}_2 \\ \vdots \\ \hat{\beta}_k \end{pmatrix} = \left(\sum_i \sum_t A_{i,t}\, Q_{i,t}{}'\right)^{-1} \left(\sum_i \sum_t A_{i,t}\, \Delta y_{i,t}\right) \tag{6.21}$$

Here, $A_{it} = \begin{pmatrix} y_{i,t-2} \\ \Delta X_{i,t,1} \\ \Delta X_{i,t,2} \\ \vdots \\ \Delta X_{i,t,k} \end{pmatrix}$; $Q_{it} = \begin{pmatrix} \Delta y_{i,t-1} \\ \Delta X_{i,t,1} \\ \Delta X_{i,t,2} \\ \vdots \\ \Delta X_{i,t,k} \end{pmatrix}$.

In order to compare the performance of Anderson and Hsiao (1981) estimator with that of GMM estimators, Arrellano and Bond (1991) perform Monte Carlo simulations and show that GMM leads efficiency gains over instrumental variables estimation method. In Arrellano and Bond (1991) approach, similar with Anderson and Hsiao (1981, 1982), first difference transformation is used to eliminate the fixed effects. But different from them, additional moment conditions are included and MA(1) with unit root error structure is considered explicitly in the estimation. Variance of differenced error term is given by (Baltagi, 2008: 149);

$$E(\Delta\varepsilon_i\, \Delta\varepsilon_i') = \sigma_\varepsilon^2 \begin{pmatrix} 2 & -1 & 0 & \dots & 0 & 0 & 0 \\ -1 & 2 & -1 & \dots & 0 & 0 & 0 \\ 0 & -1 & 2 & \dots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & 2 & -1 & 0 \\ 0 & 0 & 0 & \cdots & -1 & 2 & -1 \\ 0 & 0 & 0 & \cdots & 0 & -1 & 2 \end{pmatrix} = \sigma_\varepsilon^2 * G \tag{6.22}$$

where, $\Delta\varepsilon_i{}' = (\varepsilon_{i,3} - \varepsilon_{i,2}, \dots, \varepsilon_{i,T} - \varepsilon_{i,T-1})$.

In order to simplify the notation, we form a equation system consisting of T equations for each cross-section by stacking the time periods observations as follows;

$$\Delta y_i = \delta \Delta y_{i,-1} + \Delta x_i{}'\beta + \Delta\varepsilon_i \tag{6.23}$$

where $\Delta x_i' = (\Delta X_{i,1}\ \Delta X_{i,2} \ldots \Delta X_{i,k})$; $\beta = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_k \end{pmatrix}$; $\Delta y_i = \begin{pmatrix} \Delta y_{i,3} \\ \Delta y_{i,4} \\ \vdots \\ \Delta y_{i,T} \end{pmatrix}$;

$\Delta y_{i,-1} = \begin{pmatrix} \Delta y_{i,2} \\ \Delta y_{i,3} \\ \vdots \\ \Delta y_{i,T-1} \end{pmatrix}$; $\Delta x_i = \begin{pmatrix} \Delta x_{i,3} \\ \Delta x_{i,4} \\ \vdots \\ \Delta x_{i,T} \end{pmatrix}$; $\Delta\varepsilon_i = \begin{pmatrix} \Delta\varepsilon_{i,3} \\ \Delta\varepsilon_{i,4} \\ \vdots \\ \Delta\varepsilon_{i,T} \end{pmatrix}$.

We further stack Δy_i, $\Delta y_{i,-1}, \Delta x_i$ *and* $\Delta\varepsilon_i$ to obtain the following model;

$$\Delta y = \delta \Delta y_{-1} + \Delta x'\beta + \Delta\varepsilon \tag{6.24}$$

where, $\Delta y = \begin{pmatrix} \Delta y_1 \\ \Delta y_2 \\ \vdots \\ \Delta y_N \end{pmatrix}_{N(T-3)\times 1}$; $\Delta y_{-1} = \begin{pmatrix} \Delta y_{1,-1} \\ \Delta y_{2,-1} \\ \vdots \\ \Delta y_{N,-1} \end{pmatrix}_{N(T-3)\times 1}$; $\Delta x = \begin{pmatrix} \Delta x_1 \\ \Delta x_2 \\ \vdots \\ \Delta x_N \end{pmatrix}_{N(T-3)\times k}$;

$\Delta\varepsilon = \begin{pmatrix} \Delta\varepsilon_1 \\ \Delta\varepsilon_2 \\ \vdots \\ \Delta\varepsilon_N \end{pmatrix}_{N(T-3)\times 1}$.

We assume that all the X's are exogenous variables. By defining one instrument for each time period, variable and lag distance, based on $\frac{1}{T-2}\sum_{t=3}^{T} E(y_{i,t-2}\,\Delta\varepsilon_{i,t}) = 0$ and $\frac{1}{T-2}\sum_{t=3}^{T} E(\Delta x_{i,t}{}'\Delta\varepsilon_{i,t}) = 0$ moment conditions, following instruments are obtained (Baltagi, 2008: 149-150, 152; Erlat, 2011: 49-50; Sevestre and Trognon, 1996: 128);

$$
W_i^A = \begin{pmatrix} [y_{i,1}, x'_{i,1}, \ldots, x'_{i,T}] & & & 0 \\ & [y_{i,1}, y_{i,2}, x'_{i,1}, \ldots, x'_{i,T}] & & \\ & & \ddots & \\ 0 & & & [y_{i,1}, \ldots, y_{i,T-2}, x'_{i,1}, \ldots, x'_{i,T}] \end{pmatrix} \tag{6.25}
$$

such that $E(W_i' \, \Delta\varepsilon_i \,) = 0$. Instrument matrix can be defined as $W = \begin{pmatrix} W_1 \\ W_2 \\ \vdots \\ W_N \end{pmatrix}$.

Arrellano and Bond (1991) one-step and two-step estimators are given by the following expressions, respectively (Baltagi, 2008: 150);

$$
\widehat{\Upsilon}_{AB,1} = \begin{pmatrix} \hat{\delta} \\ \hat{\beta} \end{pmatrix} = [Q'W(W'(I_N \otimes G)W)^{-1}W'Q]^{-1} \, [Q'W(W'(I_N \otimes G)W)^{-1}W'(\Delta y)] \tag{6.26}
$$

where, Q = $(\Delta y_{-1}, \Delta x)$.

$$
\widehat{\Upsilon}_{AB,2} = \begin{pmatrix} \hat{\delta} \\ \hat{\beta} \end{pmatrix} = \left[Q'W\left(\hat{V}_N\right)^{-1}W'Q\right]^{-1} \; [Q'W\left(\hat{V}_N\right)^{-1}W'(\Delta y)] \tag{6.27}
$$

where, $\hat{V}_N = \sum_{i=1}^{N} W_i' \, \Delta\hat{\varepsilon}_i \;\; \Delta\hat{\varepsilon}_i \, 'W_i$, $\Delta\hat{\varepsilon}_i$ are the differenced residuals obtained from one-step estimation. Effiency gains obtained from two-step estimation is shown to be not so much substantial (Bond, 2002: 147). As pointed out by Harris, Mátyás and Sevestre (2008), two-step estimator can produce unreliable inference for small N, however, for this problem they recommend to use Windmeijer (2005) small sample correction for the asymptotic variance of two-step estimator.

Another solution is proposed by Arrellano and Bover (1995). According to Harris, Mátyás and Sevestre (2008), difference of Arrellano and Bover (1995) estimator is the forward orthogonal deviation that it employs to get rid of the individual effects in the random effects model, thus avoiding first order autocorrelation in the errors induced by first difference transformation. They assume that initial time period t=0 is observed and follow also GMM estimation method after transforming the Hausman and Taylor (1981) model. More information can be found in Arrellano and Bover (1995), Harris, Mátyás and Sevestre (2008) and Baltagi (2008).

Ahn and Schmidt (1995, 1997) consider additional moment conditions in addition to the ones utilized by Arellano and Bond (1991) procedure under various assumptions on initial conditions and errors in the context of random effects model and also, dynamic Hausman and Taylor model. They find evidence of efficiency gains obtained from nonlinear moment conditions. However, Ahn and Schmidt (1997) claim that simple linearized version of the estimator is also asymptotically efficient as the nonlinear GMM estimator. Baltagi (2008) provides a brief discussion.

To improve efficiency and overcome the weak instrument problem occurs when the coefficient of lagged dependent variable is close to one and relative variance of individual effects increases, Blundell and Bond (1998) suggest a system GMM estimation, thus propose additional moment conditions. They stack the models in levels and first differences following Arellano and Bover (1995) as given below (Harris, Mátyás and Sevestre, 2008: 267);

$$\binom{\Delta y}{y} = \binom{0}{\alpha} + \delta \binom{\Delta y_{-1}}{y_{-1}} + \binom{\Delta x}{x}' \beta + \binom{\Delta \varepsilon}{\varepsilon}. \tag{6.28}$$

GMM is performed to estimate the above equation system. For first differenced equation, the instruments identified by Arellano and Bond (1991) are utilized. Level variables are instrumented with lags of their own first differences in the level equation assuming that they are uncorrelated with the individual effects as mentioned by Bond (2002). Instrument set is given by the following matrix (Blundell and Bond, 1998:126);

$$W_i^B = \begin{pmatrix} W_i^A & & & 0 \\ & [\Delta y_{i,2}, \Delta x'_{i,1}, .., \Delta x'_{i,T}] & & \\ & & \ddots & \\ 0 & & & [\Delta y_{i,T-1}, \Delta x'_{i,1}, .., \Delta x'_{i,T}] \end{pmatrix} \tag{6.29}$$

based on moment conditions as, $\frac{1}{T-2}\sum_{t=3}^{T} E(y_{i,t-2}\,\Delta\varepsilon_{i,t}) = 0$; $\frac{1}{T-2}\sum_{t=3}^{T} E(\Delta x_{i,t}\,'\Delta\varepsilon_{i,t}) = 0$; $\frac{1}{T-2}\sum_{t=3}^{T} E(\Delta x_{i,t}\,'\varepsilon_{i,t}) = 0$; $\frac{1}{T-2}\sum_{t=3}^{T} E(\Delta y_{i,t-1}\,\varepsilon_{i,t}) = 0$.

Blundell and Bond (1998) perform Monte Carlo simulations to examine finite sample properties of their estimator and they conclude that for the cases of small time dimension and autoregressive coefficient which is close to one, there is substantial performance improvement over the Arellano and Bond (1991) first difference GMM estimator. After giving brief information on the estimation methods, the remaining part of this subsection is devoted to the specification tests for the dynamic panel data model.

To check for the evidence of misspecification in the model, we can test for the validity of overidentifying restrictions by Sargan-Hansen test and use Arellano and Bond (1991) autocorrelation test for testing second and higher order autocorrelation in the disturbances of the model. One can find the test statistics for the Arellano and Bond autocorrelation test in the original paper of Arellano and Bond (1991). This test is shown to have asymptotic standard normal distribution by Arellano and Bond (1991) under the null of no second order autocorrelation in the first differenced errors. Sargan-Hansen J test statistics is given by the following expression (Baltagi, 2008: 153);

$$\mathrm{J} = \Delta\,\hat{\varepsilon}' W \left(\sum_{i=1}^{N} W_i' \,\Delta\hat{\varepsilon}_i\ \ \Delta\hat{\varepsilon}_i\,' W_i\right)^{-1} W' \Delta\,\hat{\varepsilon} \sim \chi^2_{p-K-1} \tag{6.30}$$

under the null hypothesis that overidentifying restrictions are valid. p-K-1 shows the degree of overidentification and $\Delta\,\hat{\varepsilon}$ are the residuals from two-step estimation.

In our empirical study besides the above specification tests, to select the optimal number of moment conditions, we employ the method developed by Andrews and Lu (2001). Andrews and Lu (2001) suggest a procedure for model and moment selection for GMM estimation method. They develop selection criteria and downward testing procedure based on Hansen J test statistics. However, other methods are also available. Another method for the selection of moment conditions are proposed by Okui (2009). In the selection procedure of Okui (2009), for the selection of optimal number of moments, approximate mean squared error of GMM estimator obtained by Nagar (1959) approximation is minimized. Lai, Small and Liu (2008) review the studies on the model and moment selection procedures for dynamic panel data models and provide a new technique composed of two stages which uses empirical likelihood ratio and resampling. Details can be found in the original study of Lai, Small and Liu (2008). Next section is related to the estimation methods for panel cointegration model.

6.1.5. Estimation of Panel Cointegrating Relation Model

In the context of time series data, when two variables are cointegrating, OLS estimation of this cointegration relation will give super consistent estimator, however, as the "OLS estimator for the cointegrating parameter has non-normal distribution, inferences based on t statistic can be misleading" (Verbeek, 2004: 317). Dynamic OLS and Fully modified OLS estimation methods are proposed by Stock and Watson (1993) and Phillips and Hansen (1990), respectively, as an alternative to OLS estimation. Phillips and Hansen (1990) show that FMOLS estimator obtained by correcting the second order bias and long run endogeneity of explanatory variables in OLS estimator semi-parametrically, is super consistent, asymptotically unbiased and normally distributed. On the other hand, to deal with the bias and endogeneity problem, Stock and Watson (1993) suggest the inclusion of leads and lags of the explanatory variables in levels and first differences.

As noticed by Baltagi (2008), estimators for panel cointegration model show different asymptotic properties compared to ones for time series cointegration model. Different estimators can also be employed for the estimation of panel cointegration relationship. One can use pooled OLS estimator; panel group fully modified OLS (FMOLS) estimator of Pedroni (1996,2000) and Phillips and Moon (1999); panel dynamic OLS (PDOLS) estimator of Kao and Chiang (1997) and Mark and Sul (2003); pooled mean group (PMG) and mean group (MG) estimator of Pesaran et al. (1999) and Pesaran and Smith (1995); panel two-step estimator of Breitung (2005); continuous-updated fully modified (CUP-FM) estimator of Bai and Kao (2006); and Common Correlated effects mean group (CCE-MG) and pooled (CCEP) estimators of Pesaran (2006). Comparison of estimators by Kao and Chiang (2000), Pedroni (2000) and Bai and Kao (2006) shows that panel DOLS outperforms panel OLS and panel FMOLS; panel group FMOLS has better asymptotic properties than panel within dimension FMOLS; and with respect to small sample properties, CUP-FM estimator is superior over the two-step FM and OLS estimators. As in our applications, time dimension is short relative to cross section dimension, we cannot apply the methods based on SUR, therefore, in this section, we give information on only the methods applicable for our data.

Pedroni (2000) considers individual heterogeneity by including fixed effects and heterogeneous short run dynamics in the cointegrating vector. He employs fully modified OLS estimation method and obtains asymptotically unbiased and normally distributed pooled panel and group mean FMOLS estimators and besides, pooled panel FMOLS and panel FMOLS group mean t statistics that are free of nuisance parameters and have standard normal distributions. He considers the following static cointegration model given the variables ($y\ and\ x'$) are cointegrated for each i;

$$y_{it} = \alpha_i + x_{it}'\beta + \varepsilon_{it} \tag{6.31}$$

where, $x_{it} = x_{it-1} + u_{it}$, i.e., he assumes $\{x_{it}\}$ are K×1 I(1) processes for all i. He assumes that multivariate functional central limit theorem and cross-sectional independence holds but recommends using common time dummies to account for possible cross-sectional dependency. Model does not allow for the cointegration among $x_i's$ and not put any restriction on the exogeneity of $x's$. Under this setting, he shows that the OLS estimator is asymptotically biased and asymptotic distribution depends on nuisance parameters. From investigation of small sample properties by Monte Carlo simulations, he finds that in small samples where time dimension is as large as the cross sectional dimension, size distortions are relatively small for group mean test statistics. Breitung (2005) critizes the FMOLS estimation in two points; first, the performance of nonparametric approach employed in FMOLS estimation for small samples and the cases where the process has MA root close to one may be poor; and secondly, this approach is based on the assumption that there is only one cointegrating relation. Breitung (2005) suggests two-step parametric estimation of panel cointegration models in the context of cointegrated panel VAR(p) set-up assuming homogeneous long run relation based on previous studies of Ahn and Reinsel (1990), Engle and Yoo (1991) and Saikkonen (1992). He also demonstrates that the method can be extended to account for contemporaneous cross-section correlation. In the first step, equation is estimated for each cross-section using Johansen (1988, 1991) MLH estimator or Engle and Granger (1987) two step estimator in order to obtain short run parameters specific to each individual and in the second step, using pooled regression, estimates of common long run parameters are obtained by OLS. He shows that the estimator obtained is asymptotically efficient and normally distributed, besides, results of Monte Carlo experiment indicate that in small samples, two-step estimator outperforms FMOLS and DOLS estimator. The following cointegrated VAR(1) model in VECM form is considered in the paper;

$$\Delta y_{it} = \alpha_i \beta' y_{it-1} + \varepsilon_{it}\,;\ i = 1, .., N \ and \ t = 1, \dots, T; E(\varepsilon_{it}) = 0 \ and \ \Sigma_i = E(\varepsilon_{it}\, \varepsilon_{it}') \tag{6.32}$$

On the other hand, as an alternative to FMOLS, Kao and Chiang (2000) develop panel data version of DOLS estimator proposed by Saikkonen (1991) and Stock and Watson (1993). They examine and compare the small sample properties and performance of panel estimators based on OLS, FMOLS and DOLS. Results of their study indicate substantial bias in OLS estimator and superiority of DOLS over OLS and FMOLS. Mark and Sul (2003) also investigate the properties of panel DOLS based on a model which takes individual heterogeneity and cross-sectional dependence into account by including individual fixed effects, individual time trends, common time effects and individual specific short run dynamics. The model is given by;

$$y_{it} = \alpha_i + \lambda_i t + \theta_t + x_{it}{}'\beta + \varepsilon_{it} \tag{6.33}$$

$$x_{it} = x_{it-1} + u_{it}$$

where $\{x_{it}\}$ are K×1 I(1) processes for all i. In this model the cointegrating vector (1, - β) is assumed to be same across cross-sectional units. For the error dynamics, $(\varepsilon_{it}, u_{it})$ is assumed to follow a MA(q) process and to be cross-sectionally independent. Endogeneity resulted from the pth order correlation between u_{it} and ε_{it} is corrected by adding p lags and leads of Δx_{it} into the cointegration equation. They show that the PDOLS estimator is asymptotically mixed normally distributed and Wald statistics to test for linear restrictions on PDOLS estimator has limiting chi-square distribution. From the comparison of small sample properties between PDOLS and single equation DOLS based on Monte Carlo experiments considering the individual fixed effects and cross-sectional dependence, they reveal that "panel DOLS is much more precise than single-equation DOLS" (Mark and Sul, 2003: 674). They conclude that PDOLS estimation method provides parametric, computationally simple and precise estimators and the resultant test statistics have asymptotic standard distributions.

Bai and Kao (2006) propose nonparametric continuous-updated fully modified (CUP-FM) estimator in order to deal with cross-sectional dependence by introducing a factor structure into the panel cointegration model. The model extended by including a factor model for the error term is as follows;

$$y_{it} = \alpha_i + x_{it}'\beta + \varepsilon_{it} \tag{6.34}$$
$$x_{it} = x_{it-1} + u_{it}$$
$$\varepsilon_{it} = \lambda_i' F_t + e_{it}$$

where, y_{it} is cointegrated with x_{it}. $\{x_{it}\}$ are K×1 I(1) processes for all i. In order to consider cross-sectional dependence, ε_{it} is modeled by a factor model in which, F_t *and* λ_i are the vectors of common factors and factor loadings, respectively. They examine the limiting distributions of OLS, bias-corrected OLS, FM and feasible FM estimators and show that they all have asymptotic normal distributions. CUP-FM estimator is obtained from the recursive estimation of parameters, long-run covariance matrix and factor loadings. The asymptotic distributions of the Wald and t test statistics for FM estimators are shown to be chi-square and standard normal. They perform Monte Carlo experiments and find that in the small samples, CUP-FM estimator outperforms both OLS and two-step FM estimators.

In panel cointegration relation estimation of our model, for comparison purposes, we employ additional estimators which are mean group (MG) estimator of Pesaran et al. (1999) and Pesaran and Smith (1995), Common Correlated effects mean group (CCE-MG) and pooled (CCEP) estimators of Pesaran (2006). In the next section, details and properties for these estimators are given.

6.1.6. Estimation of Panel Error Correction Model

To distinguish between the long-run and short-run relation between y_{it} and x_{it}, error correction model is employed. Existence of cointegration relation implies the validity of error correction representation of the data. This result is based on the Granger representation theorem. Pesaran and Smith (1995) and Pesaran et al. (1999) propose mean group (MGE) and pooled MGE (PMGE) estimators to estimate an panel error correction model given by the reparametrization of following panel ARDL$(p, q, \ldots, q)$ model (Pesaran et al., 1999: 623);

$$y_{it} = \alpha_i + \sum_{j=1}^{p} \beta_{ij}\, y_{it-j} + \sum_{j=0}^{q} \delta_{ij}{}'\, x_{it-j} + \varepsilon_{it} \tag{6.35}$$

They assume common p, T and q across cross sections and regressors. Reparametrization of the above equation give the following ECM expression (Pesaran et al., 1999: 623);

$$\Delta y_{it} = \varphi_i(y_{it-1} - \alpha_i^* - \delta_i^{*\prime} x_{it}) + \sum_{j=1}^{p-1} \beta_{ij}{}^{**}\, \Delta y_{it-j} + \sum_{j=0}^{q-1} \delta_{ij}{}^{**}{}'\Delta x_{it-j} + \varepsilon_{it} \tag{6.36}$$

where,

$\varphi_i = -\left(1 - \sum_{j=1}^{p} \beta_{ij}\right)$; $\alpha_i^* = -\alpha_i/\varphi_i$; $\delta_i^* = -\sum_{j=0}^{q} \delta_{ij}/\varphi_i$;

$\delta_{ij}^{**} = -\sum_{m=j+1}^{q} \delta_{im}$; $\beta_{ij}^{**} = -\sum_{m=j+1}^{p} \beta_{im}$; i = 1,2,...,N; t = 1, 2,..,T; j = 1,...,p-1 for β_{ij}^{**} and ; j = 1,...,q-1 for δ_{ij}^{**}. ε_{it} is independently distributed error term across i and t. $\varepsilon_{it} \sim (0, \sigma_i^2)$. φ_i is the coefficient on error correction term determining the speed of adjustment to the equilibrium. $\beta_{ij}{}^{**}$ *and* $\delta_{ij}{}^{**\prime}$ are short run coefficients, whereas, $\delta_i^{*\prime}$ are long run coefficients. α_i is the fixed effects.

Mean group estimator of Pesaran and Smith (1995) is based on the separate OLS estimation of cointegration and error correction model for each i and then simply, taking average over cross-sections, thus they allow the coefficients and error variances to vary across cross-sections using random coefficient model in which parameter for each i is taken as random. They show that this yields consistent estimates for the average of parameters, call θ. Mean group estimator of $\theta = E(\theta_i)$ and consistent estimator of its variance are given by the following expression (Pesaran, Smith and Im, 1996: 157);

$$\hat{\theta}_{MG} = \frac{1}{N}\sum_{i=1}^{N} \hat{\theta}_i \text{ and } \hat{V}\left(\hat{\theta}_{MG}\right) = \frac{1}{N(N-1)}\sum_{i=1}^{N}(\hat{\theta}_i - \hat{\theta}_{MG})(\hat{\theta}_i - \hat{\theta}_{MG})' \tag{6.37}$$

Asymptotic distribution of mean group estimator is shown to be normal by Pesaran et al. (1999). However, Pesaran et al. (1999) critizes MG estimator as it does not consider the homogeneity of some parameters across cross-sections. They suggest Pooled MGE (PMGE) estimator in which they impose homogeneity of long-run coefficients and allow heterogeneous intercepts, short run coefficients and error variances across cross-sections. Stacking the time series observations for each i and assuming long run homogeneity of coefficients on x_{it} $(such\ that\ \theta_i = \theta)$ and the stability of ARDL(p,q,..,q) model which ensures the existence of cointegration between y_{it} and x_{it}, they obtain a compact form of the model given as follows;

$$\Delta y_i = \varphi_i\left(y_{i,-1} - X_i\theta\right) + W_i\kappa_i + \varepsilon_i,\ \text{i=1,..,N} \tag{6.38}$$

where, $W_i = (\{\Delta y_{i,-j}\}_{j=-1}^{-p+1}; \{\Delta x_{i,-j}\}_{j=0}^{-q+1}); \kappa_i = (\alpha_i; \{\beta_{ij}{}^{**}\}_{j=1}^{p-1}; \{\delta_{ij}{}^{**\prime}\}_{l=0}^{q-1})$ and $\text{Var}(\varepsilon_{it}) = \sigma_i^2$. They follow maximum likelihood approach to estimate this equation assuming normality and concentrated log-likelihood function given by (Pesaran et al., 1999: 624);

$$l_T(\theta', \varphi', \sigma') = -\frac{T}{2}\sum_{i=1}^{N} ln2\pi\sigma_i^2 - \sum_{i=1}^{N}\frac{1}{2\sigma_i^2}\left[\Delta y_i - \varphi_i\left(y_{i,-1} - X_i\theta\right)\right]' H_i\left[\Delta y_i - \varphi_i\left(y_{i,-1} - X_i\theta\right)\right] \tag{6.39}$$

where, $\varphi = \{\varphi_i\}_{i=1}^{N};\ \sigma = \{\sigma_i^2\}_{i=1}^{N};\ H_i = I_T - W_i(W_i'\ W_i)^{-1}W_i'$.

They suggest to use Newton-Raphson or Back-Substitution algorithms to obtain PMG estimator from the maximization of $l_T(\theta', \varphi', \sigma')$ with respect to $(\theta', \varphi', \sigma')$. Under certain assumptions and stationary regressors, PMG estimator is proved to be consistent and asymptotically normally distributed for fixed N and as T→ ∞. If the regressors are I(1), again under certain assumptions, Pesaran et al. (1999) establish that PMG estimator is consistent and has asymptotic mixture normal distribution as

T→ ∞ for fixed N. In order to test for the homogeneity of long-run coefficients, Pesaran et. al. (1999) suggests using Hausman type test. Hausman test statistic is shown as below (Baltagi, 2008:73);

$$m = \hat{q}'[V(\hat{q})]^{-1}\hat{q} \sim^{A} \chi_K^2 \tag{6.40}$$

under the null hypothesis of long-run slope homogeneity. K is the dimension of vector θ. Here, $\hat{q} = \hat{\theta}_{PMG} - \hat{\theta}_{MG}$ and $V(\hat{q}) = V(\hat{\theta}_{MG}) - V(\hat{\theta}_{PMG})$. Under the assumption of long-run slope homogeneity, pooled estimators are consistent and efficient but inconsistent under heterogeneity; and although mean group estimator is consistent estimator of the mean of long run coefficients under homogeneity and heterogeneity, it is inefficient under null (Pesaran et al., 1999: 627).

For cross-sectional dependence problem, Pesaran (2006) develops Common Correlated effects mean group (CCE-MG) and pooled (CCEP) estimators. Holly, Pesaran and Yamagata (2010) employ these estimators for the estimation of panel error correction model. Their procedure consists of two stages: in the first stage, they use pooled and mean group CCE estimator to estimate the cointegration relation in equation (6.41) and test for the unit root in the residuals ($\hat{u}_{it}$) of this estimation by CIPS test; in the second stage, by using CCE-MG and CCEP estimators, they estimate a panel error correction model in equation (6.42) given the variables are cointegrated assuming homogeneous long-run relation across cross sections such that cointegrating vector is (1 -1).

$$y_{it} = \alpha_i + \beta_i{}'x_{it} + u_{it} \tag{6.41}$$

where $u_{it} = \sum_{\ell=1}^{m_1} \xi_{1i\ell} f_{1\ell t} + \vartheta_{1it}$ such that multifactor error structure is allowed.

$$\Delta y_{it} = \mu_i + \varphi_i\left(y_{it-1} - \widehat{\beta}' x_{it-1}\right) + \beta_{i1}{}^{**}\Delta y_{it-1} + \delta_{i0}{}^{**}{}'\Delta x_{it} + \delta_{i1}{}^{**}{}'\Delta x_{it-1} + \varepsilon_{it} \tag{6.42}$$

where, $\varepsilon_{it} = \sum_{\ell=1}^{m_2} \xi_{2i\ell} f_{2\ell t} + \vartheta_{2it}$. Generally, in order to get rid of the different effects of unobserved common factors, Pesaran (2006) suggests to extend the model by including the cross-sectional averages of dependent variable and regressors as additional regressors to the model. He considers the following equation systems (6.43) in the context of linear heterogeneous model given in (6.44) and model for x_{it} (6.45) (Pesaran, 2006: 4);

$$z_{it} = \binom{y_{it}}{x_{it}} = B_i' d_t + C_i' f_t + u_{it} \qquad (6.43)$$

where,

$$y_{it} = \alpha_i' d_t + \beta_i' x_{it} + e_{it} \quad \text{with } e_{it} = \gamma_i' f_t + \varepsilon_{it} \qquad (6.44)$$

here, d_t is vector of observed common effects, x_{it} is the vector of observed regressors, f_t is the vector of unobserved common factors which can be correlated with d_t and x_{it}; and ε_{it} is the idionsyncratic errors independent of d_t and x_{it}. Further he assumes that x_{it} can be modeled by the following structure in which A_i and Γ_i are factor loading matrices, v_{it} are the specific components independent of (f_t, d_t) and across i and (f_t, d_t, v_{it}) are all covariance stationary (Pesaran, 2006: 4);

$$x_{it} = A_i' d_t + \Gamma_i' f_t + v_{it} \qquad (6.45)$$

To show how $\bar{h}_t = (d_t' \, \bar{z}_t')'$ can be used as observable proxies for f_t, Pesaran (2006) proceed by taking the cross section averages of equation for z_{it};

$$\bar{z}_t = \bar{B}' d_t + \bar{C}' f_t + \bar{u}_t \qquad (6.46)$$

Under the assumption that the rank of $\bar{C}$ is not greater than k+1 where k is the number of regressors, he obtains f_t by multiplying both sides of the equation for $\bar{z}_t$ by $\bar{C}$ and solve for f_t as;

$$f_t = (\bar{C}\bar{C}')^{-1}\bar{C}(\bar{z}_t - \bar{B}'d_t - \bar{u}_t) \quad (6.47)$$

He further shows that $\bar{u}_t \rightarrow^{q.m.} 0 \; for \; each \; t \; and \; \bar{C} \rightarrow C \;\; as \; N \rightarrow \infty,$ and also as $N \rightarrow \infty, f_t - (CC')^{-1}C(\bar{z}_t - \bar{B}'d_t) \rightarrow^{p} 0$. Therefore, augmented regression model in which the effects of unobserved common factors are filtered asymptotically as $N \rightarrow \infty$, is given by the following expression;

$$y_{it} \; = \; \alpha_i^{'} d_t + \beta_i{}' x_{it} + g_i{}' \bar{z}_t + \varepsilon_{it} \quad (6.48)$$

Individual CCE estimator of β_i obtained from applying least squares to the above model is shown as below, (Pesaran, 2006:9);

$$\hat{\beta}_{i,CCE} = (X_i{}'\bar{M}X_i)^{-1}(X_i{}'\bar{M}y_i) \quad (6.49)$$

here, $X_i = (X_{i1}, X_{i2}, \dots, X_{iT})$; $X_i = (y_{i1}, y_{i2}, \dots, y_{iT})$; $\bar{M} = I_T - \bar{H}\,(\bar{H}'\bar{H}\,)^{-1}\bar{H}'$; $\bar{H} = (D, \bar{Z}\,)$; $(D,\; \bar{Z}\,)$ are the observations on $\bar{h}_t$.

The mean group CCE estimator of β under the assumption that E$(\beta_i) = \beta$ is the average of $\hat{\beta}_i' s$ (Pesaran, 2006: 14);

$$\hat{\beta}_{CCE-MG} = \frac{1}{N}\sum_{i=1}^{N} \hat{\beta}_{i,CCE} \quad (6.50)$$

Assuming common slope coefficients and error variances across cross-sections, Pesaran (2006) propose pooled CCE estimator of β as shown below;

$$\hat{\beta}_{CCEP} = (\sum_{i=1}^{N} X_i{}'\bar{M}X_i)^{-1} \sum_{i=1}^{N} X_i{}'\bar{M}y_i \quad (6.51)$$

Pesaran (2006) shows that under certain assumptions, $\hat{\beta}_i$ is consistent estimator of β_i; $\hat{\beta}_{CCE-MG}$ and $\hat{\beta}_{CCEP}$ are asymptotically unbiased for β; and all have asymptotic normal distributions. He also points out that small sample properties of mean group and pooled CCE estimators are satisfactory. In the following section, we discuss the properties of various panel unit root and cointegration tests.

6.2. Panel Unit Root and Cointegration Tests

In this section, we discuss various types of panel unit root and cointegration tests. When N is small and T is large relatively, the tests can be carried out in the context of Seemingly Unrelated Regressions. For example, Abuaf and Gorion (1990), Taylor and Sarno (1998) and Breuer, McNown and Wallace (2001) develop panel unit root tests using SUR equations assuming either homogeneity or heterogeneity across cross-sectional units. But in the cases where T is not as large as N, tests become much more complicated. Breitung and Pesaran (2008) summarize the complications associated with using the panel data for unit root and cointegration tests. They focus on the problems of unobserved heterogeneity, cross-sectional dependency, complicated asymptotic theory, possibility of cross section cointegration besides within group cointegration and interpretation difficulties of test results. We group the tests according to the assumption of cross-sectional independence. In the literature, the tests that assume cross-sectional independence are called first generation tests, whereas, the second generation tests allow for cross-sectional dependence. In order to test for unit root and cointegration in panel data context, many theoretical and empirical studies have been done in the literature. The panel unit root tests that we explain in section 6.2.1, include the ones proposed by Levin, Lin and Chu (2002), Breitung (2000), Im, Pesaran and Shin (2003), Maddala and Wu (1999), Choi (2001), Hadri (2000), Pesaran (2007) and Carrion-i-Silvestre et al. (2005). Then, in section 6.2.2, we give brief information on panel cointegration tests of Pedroni (1999, 2004), Kao (1999), Larsson, Lyhagen and Löthgren (2001), Westerlund (2006) and Westerlund (2007). We only summarize the procedure of various tests; for detailed information on the tests, one can refer to the original papers and also surveys and studies of Baltagi and Kao (2000), Erlat and Özdemir (2003), Hlouskova and Wagner (2005), Barbieri (2006), Örsal (2007), Baltagi (2008), Breitung and Pesaran (2008) and Erlat (2009).

6.2.1. Panel Unit Root Tests

Beginning by the first panel unit root test application of Abuaf and Gorion (1990) to real exchange rate and theoretical studies of Quah (1990, 1992, 1994), Levin and Lin (1992, 1993) and Breitung and Meyer (1994), many researchers have made various theoretical and empirical contributions to the literature of panel unit root tests. All these studies show that as the panel unit root tests combine the information over time and cross sectional dimensions, there is substantial power increase over the time-series unit root tests which only consider the time dimension of the data and has low power, thus, too often indicate that a series contains a unit root (Enders, 1995: 251). In panel unit root testing, the following general model is considered unless otherwise is stated (Baltagi, 2008: 276);

$$\Delta y_{it} = \rho_i y_{it-1} + \sum_{L=1}^{p_i} \theta_{iL} \Delta y_{it-L} + \alpha_{im} d_{mt} + \varepsilon_{it} \quad , \text{m=1, 2, 3} \qquad (6.52)$$

where, d_{mt} is the vector of deterministic components.

$$\text{m} = \begin{cases} 1 & \text{if} \quad \text{there is no any deterministic term} \\ 2 & \text{if} \quad \text{there is only individual effects} \\ 3 & \text{if} \quad \text{there is both individual effects and time trends} \end{cases}$$

In section 6.2.1.1, we compare first generation panel unit root tests under the assumption of cross-sectional independence and in section 6.2.1.2, relaxing this assumption and thus, allowing for cross-sectional dependence, second generation panel unit root tests are discussed.

6.2.1.1. First Generation Panel Unit Root Tests

Assuming that cross-sections are independent, Levin, Lin and Chu (LLC) (2002), Breitung (2000), Im, Pesaran and Shin (IPS) (2003), Maddala and Wu (1999), Choi (2001) and Hadri (2000) propose various methods to test for unit roots in the panel data. We can further classify the tests according to their null hypothesis as nonstationarity tests and stationarity tests as in the time series tests. In all the tests except Hadri (2000)'s test, null hypothesis of unit root is tested against the alternative of stationarity. Alternative classification can be based on the assumption related to the unit root process. Levin, Lin and Chu (2002), Breitung (2000) and Hadri (2000) assumes common unit root process across cross-sections such that in equation (6.52), $\rho_i = \rho$. However, Im, Pesaran and Shin (2003), Maddala and Wu (1999) and Choi (2001) do not put any restriction on the unit root process, thus allow for individual unit root processes. In this section, we give brief information on all the aforementioned tests and compare their properties.

Levin, Lin and Chu (2002) develop their test upon the studies of Quah (1992, 1994), Breitung and Mayer (1994) and Levin and Chu (1992, 1993). They allow individual effects and time trends; and heterogeneous autocorrelation for the error terms. They consider the following model allowing for the different lag lengths for the difference terms in (6.53) and test the null against the alternative hypothesis in (6.54);

$$\Delta y_{it} = \rho y_{it-1} + \sum_{L=1}^{p_i} \theta_{iL} \Delta y_{it-L} + \alpha_{im} d_{mt} + \varepsilon_{it} \tag{6.53}$$

$$H_0: \rho = 0 \text{ against } H_1: \rho \neq 0 \tag{6.54}$$

Their test is based on three-step procedure. In the first step, ADF regressions for each cross-section are performed. Second step deals with the estimation of the ratio of long-run to short-run standard deviations. Panel test statistics are computed in the third step running the following pooled regression (Baltagi, 2008: 276; Levin, Lin and Chu, 2002: 7);

$$\tilde{e}_{it} = \rho \tilde{v}_{it-1} + \tilde{\varepsilon}_{it}, \tag{6.55}$$

with $N\tilde{T}$ observations where, $\tilde{T} = T - \bar{p} - 1$ is the average observation number per cross-section in the panel and $\bar{p} = \frac{1}{N}\sum_{i=1}^{N} p_i$. Here, $\tilde{e}_{it} = \frac{\hat{e}_{it}}{\hat{\sigma}_{\varepsilon i}}$; $\tilde{v}_{it-1} = \frac{\hat{v}_{it-1}}{\hat{\sigma}_{\varepsilon i}}$. $\hat{e}_{it}$ and $\hat{v}_{it-1}$ are the residuals obtained from the regressions of Δy_{it} and y_{it-1} on Δy_{it-L}, and d_{mt}, respectively; $\mathrm{L} = 1,2, \ldots, \mathrm{p_i}$; $\mathrm{m} = 1,2,3$. $\hat{\sigma}_{\varepsilon i}^2$ are calculated either from the regression of $\hat{e}_{it}$ on $\hat{v}_{it-1}$ or from individual ADF regressions. In equation (6.55), t-ratio to test for $H_0: \rho = 0$ give the panel unit root test statistics as follows;

$$t_\rho = \frac{\hat{\rho}}{STD(\hat{\rho})} \tag{6.56}$$

Levin, Lin and Chu (2002) show that under null hypothesis, t_ρ has a asymptotic normal distribution for a model without deterministic terms; for other cases, it diverges to negative infinity. Therefore, they suggest using the following adjusted t-statistic;

$$t_\rho^* = \frac{t_\rho - N\tilde{T}\hat{S}_N \hat{\sigma}_{\tilde{\varepsilon}}^{-2} STD(\hat{\rho}) \mu_{m\tilde{T}}^*}{\sigma_{m\tilde{T}}^*} \sim N(0,1) \text{ asympotically, under null hypothesis} \tag{6.56'}$$

In this expression, $\mu_{m\tilde{T}}^*$ and $\sigma_{m\tilde{T}}^*$ are the mean and standard deviation adjustments which can be found in Levin, Lin and Chu (2002)'s paper for different deterministic term specification and time series dimension. Expressions for $\hat{\sigma}_{\tilde{\varepsilon}}^2, \hat{\rho}, STD(\hat{\rho}), \hat{S}_N$ *and* $\hat{\sigma}_{yi}^2$ are given in equations (6.57), (6.58), (6.59), (6.60) and (6.61);

$$\hat{\sigma}_{\tilde{\varepsilon}}^2 = \left[\frac{1}{N\tilde{T}} \sum_{i=1}^N \sum_{t=2+p_i}^T (\tilde{e}_{it} - \hat{\rho}\tilde{v}_{it-1})^2\right] \tag{6.57}$$

$$\hat{\rho} = \frac{\sum_{i=1}^N \sum_{t=2+p_i}^T \tilde{v}_{it-1}\tilde{e}_{it}}{\sum_{i=1}^N \sum_{t=2+p_i}^T \tilde{v}_{it-1}{}^2} \tag{6.58}$$

$$STD(\hat{\rho}) = \sqrt{\hat{\sigma}_{\tilde{\varepsilon}}^2 \left[\sum_{i=1}^N \sum_{t=2+p_i}^T \tilde{v}_{it-1}{}^2\right]^{-1}} \tag{6.59}$$

$$\hat{S}_N = \left[\frac{1}{N} \sum_{i=1}^N \hat{s}_i\right] \tag{6.60}$$

where, $\hat{s}_i = \hat{\sigma}_{yi}/\hat{\sigma}_{\varepsilon i}$. σ_{yi}^2 is the long run variance and estimate of it for the model without any deterministic terms is given as below;

$$\hat{\sigma}_{yi}^2 = \frac{1}{T-1}\sum_{t=2}^{T}\Delta y_{it}^2 + 2\sum_{L=1}^{\bar{K}} w_{\bar{K}L}\left[\frac{1}{T-1}\sum_{t=2+L}^{T}\Delta y_{it}\,\Delta y_{it-L}\right] \tag{6.61}$$

$w_{\bar{K}L}$ are the sample covariance weights and depends on kernel choice.

Breitung (2000) analyzes the local power properties of tests suggested by Levin and Lin (1993) and Im, Pesaran and Shin (1997, 2003) and shows that bias adjustment employed in the tests may cause severe power loss. He also assumes common unit root process as in LLC test, therefore he tests the null hypothesis against homogeneous alternative given in (6.54). However, different from tests of Levin, Lin and Chu (2002) and Im, Pesaran and Shin (2003), he proposes a test which does not require bias correction. First step of the test is similar to the test of LLC but to obtain standardized residuals, $\tilde{e}_{i,t} = \frac{\hat{e}_{i,t}}{\hat{\sigma}_{\varepsilon,i}}$; $\tilde{v}_{i,t-1} = \frac{\hat{v}_{i,t-1}}{\hat{\sigma}_{\varepsilon,i}}$, thus $\hat{e}_{i,t}$ and $\hat{v}_{i,t-1}$; excluding the deterministic terms, the regressions of $\Delta y_{i,t}$ and $y_{i,t-1}$ on $\Delta y_{i,t-L}$; $\mathrm{L} = 1,2,\dots,\mathrm{p_i}$ are performed. Further, $\tilde{e}_{i,t}$ and $\tilde{v}_{i,t-1}$ are transformed using forward orthogonalization to obtain $e_{i,t}^*$ and $v_{i,t-1}^*$. To obtain a test statistic for $H_0\colon \rho = 0$; in the last step, he runs the following pooled regression of $e_{i,t}^*$ on $v_{i,t-1}^*$;

$$e_{i,t}^* = \rho v_{i,t-1}^* + \varepsilon_{i,t}^* \tag{6.62}$$

He shows that under null hypothesis, t-statistic follows a asymptotic standard normal distribution. Another difference of this test from LLC is that there is no need for kernel computations.

Im, Pesaran and Shin (2003) consider the heterogeneity in the unit root process and thus, the following hypotheses in their test in which for the alternative hypothesis, some portion of the cross-sections are allowed to have nonstationary time series;

$H_0\colon \rho_i = 0$ for all i, (6.63)

against

$$H_1: \begin{cases} \rho_i < 0 & for \quad i = 1,2,3,\ldots, N_1 \\ \rho_i = 0 & for \quad i = N_1 + 1, \ldots, N \end{cases} \text{ such that } lim_{N\to\infty}\left({N_1}/{N}\right) = \delta$$

where $0 < \delta \leq 1$.

For each cross-section i, ADF tests are performed by running the regression in (6.52) and testing the null hypothesis that $H_0: \rho_i = 0$. After obtaining the individual test statistics which are $t_{\rho_i} = \left({\hat{\rho}_i}/{STD(\hat{\rho}_i)}\right)$, averaging individual t-ratios over i gives the following IPS t-bar statistic;

$$\bar{t} = \left({1}/{N}\right) \sum_{i=1}^{N} t_{\rho_i}, \tag{6.64}$$

Im, Pesaran and Shin (2003) obtain a asymptotically standard normal statistic under H_0 using an appropriate standardization of IPS t-bar statistic. The standardized statistic is as follows;

$$t_{IPS} = \frac{\sqrt{N}\left(\bar{t} - ({1}/{N}) \sum_{i=1}^{N} E(t_{\rho_i})\right)}{\sqrt{({1}/{N}) \sum_{i=1}^{N} var(t_{\rho_i})}} \sim \text{N(0, 1) asymptotically, under null of nonstationarity} \tag{6.65}$$

Im, Pesaran and Shin (2003) simulate and tabulate the values of $E(t_{\rho_i})$ and $var(t_{\rho_i})$ for various values of T and p_i under different specifications. They show that for small samples, IPS test outperforms the LLC test given a large lag order in ADF regressions.

Alternative nonstationarity tests are suggested by Maddala and Wu (1999) and Choi (2001) assuming individual unit root processes based on Fisher (1932) non-parametric approach. The basic logic is that instead of averaging the t-ratios of individual ADF tests, Fisher type tests combine the p-values of individual nonstationarity unit root tests, P_i. The test is given by (Baltagi, 2008: 281);

$$P = -2\sum_{i=1}^{N} ln\text{P}_\text{i} \sim \chi_{2N} \text{ for finite N and } T_i \to \infty \tag{6.66}$$

In this framework, additionally, Choi (2001) proposes asymptotic standard normal inverse normal and modified P test statistics given in equations (6.67) and (6.68), respectively;

$$Z = \frac{1}{\sqrt{N}}\sum_{i=1}^{N} \Phi^{-1}\,(\text{P}_\text{i}) \sim N(0,1) as\ T_i \to \infty\ for\ all\ i \tag{6.67}$$

here, Φ is the cumulative standard normal distribution function.

$$P_m = \frac{1}{2\sqrt{N}}\sum_{i=1}^{N}(-2ln\text{P}_\text{i} - 2) \sim N(0,1) \text{ for } (T_i, N \to \infty)_{seq} \tag{6.68}$$

Hadri (2000) extends the KPSS stationarity test employed for time series data to the panel data assuming common unit root process under the alternative hypothesis. It is a residual-based LM test in which under null hypothesis, it is assumed that all the series in the panel are stationary. Hadri's test is based on following structural model with and without trend;

$$y_{it} = r_{it} + \alpha_{im}d_{mt} + \varepsilon_{it}, \text{ m=1, 2; i=1,...,N and t=1,...,T} \tag{6.69}$$

where, $r_{it} = r_{it-1} + u_{it}$; $\varepsilon_{it} \sim iiN(0,\ \sigma_\varepsilon^2)$ and $u_{it} \sim iiN(0,\ \sigma_u^2)$ across i and over t; $d_{m1} = \emptyset$; $d_{m2} = \{t\}$. If m=2, then the model includes a trend term, otherwise, we have a model without a trend. In this model, under null of stationarity, variance of random walk needs to be zero. Using back substitution and imposing $H_0\colon \sigma_u^2 = 0$, we obtain following expression which implies that y_{it} is stationarity around a constant (or a trend) for the model without (with) trend;

$$y_{it} = r_{i0} + \alpha_{im}d_{mt} + \varepsilon_{it} \tag{6.70}$$

The above expression under $H_1\colon \sigma_u^2 > 0$ is as follows;

$$y_{it} = r_{i0} + \alpha_{im} d_{mt} + \sum_{s=1}^{t} u_{is} + \varepsilon_{it} \tag{6.71}$$

LM statistic to test for stationarity under homoscedasticity assumption is given by (Baltagi, 2008: 282);

$$LM_1 = \left(\frac{1}{NT^2}\right)\left(\frac{\sum_{i=1}^{N}\sum_{t=1}^{T} S_{it}^2}{\hat{\sigma}_\varepsilon^2}\right) \tag{6.72}$$

here, S_{it} is the partial sum of residuals obtained from the OLS estimation of the (6.71) and $\hat{\sigma}_\varepsilon^2$ is consistent estimate of σ_ε^2 under $H_0: \sigma_u^2 = 0$.

To account for heteroscedasticity across i, Hadri (2000) propose another version of the statistic given in equation (6.73).

$$LM_2 = \left(\frac{1}{NT^2}\right)\left(\sum_{i=1}^{N}\sum_{t=1}^{T} \frac{S_{it}^2}{\hat{\sigma}_{\varepsilon i}^2}\right) \tag{6.73}$$

He shows that both LM statistics have asymptotic standard normal distributions after some manipulations;

$$Z = \frac{\sqrt{N}(LM - \xi)}{\zeta} \sim N(0,1) \text{ under null hypothesis.} \tag{6.74}$$

For the model without (with) trend, $\xi = \frac{1}{6}\ and\ \zeta = \frac{1}{45}\ \left(\xi = \frac{1}{15}\ and\ \zeta = \frac{11}{6300}\right)$. Im, Pesaran and Shin (1997, 2003), Karlsson and Lothgren (1999), Maddala and Wu (1999), Breitung (2000), Choi (2001), Levin et al. (2002), Banerjee, Marcellino and Osbat (2005) and Hlouskova and Wagner (2006) conduct various simulations to compare the finite sample performance of the above tests. Detailed information is presented in the studies mentioned.

Main drawback of all the tests that we review up to here, is the assumption of cross-sectional independence. In the next section, we continue with the second generation panel unit root tests relaxing this assumption.

6.2.1.2. Second Generation Panel Unit Root Tests

Ignoring the cross-sectional dependence can cause the panel unit root test to over reject the nonstationarity as shown by O'Connell (1998). Cross-sectional dependence can be a result of many factors such as omitted observed common factors, spatial spillover effects, unobserved common factors or general residual interdependence remained after considering all the observed and unobserved common effects which are mentioned by Breitung and Pesaran (2008). To deal with cross-sectional dependency, Levin, Lin and Chu (2002) and Im, Pesaran and Shin (2003) suggest the application of first generation unit root tests to cross-sectionally demeaned series. However, this may only reduce the cross-sectional correlation as shown by Luintel (2001). Abuaf and Jorion (1990), O'Connell (1998), Wu and Wu (1998), Taylor and Sarno (1998) and Breuer, McNown and Wallace (2001) solve the problem in the context of SUR methods. SUR-based methods can be used for the cases where T>N; otherwise, estimated covariance matrix is singular. Maddala and Wu (1999) and Chang (2004) suggest bootstrap procedure in order to improve size properties of SUR-based tests (Breitung and Pesaran, 2008: 297). As an alternative approach, cross-sectional dependency is modeled using common factor structure. This approach is considered by Choi (2002), Phillips and Sul (2003), Moon and Perron (2004), Bai and Ng (2004) and Pesaran (2007). Choi (2002), Phillips and Sul (2003) and Moon and Perron (2004) first, remove the common factors by employing different methods such as time series and cross-sectional demeaning, moment method and principal components analysis and then, suggest various unit root tests for the defactored series. "On the other hand, Bai and Ng (2004) decompose the series by employing principal component analysis and suggest testing separately the presence of unit root in the common and individual components" (Hurlin and Mignon, 2006: 8-9). Among these studies, Pesaran (2007) introduces a very simple procedure to account for cross-sectional dependency in panel unit root testing. Therefore, in our analysis, we employ this technique and here, we review this test only.

Pesaran (2007) suggests to augment the usual ADF regression with lagged cross-sectional means ($\bar{y}_{t-1} = N^{-1}\sum_{i=1}^{N} y_{i,t-1}$), cross section averages of first differences ($\Delta\bar{y}_t$) and lagged first differences of cross sectional mean ($\Delta\bar{y}_{t-L}$) based on procedure defined in Pesaran (2006). He considers one common factor structure for the error term in which unobserved common factor has differential effects across cross sections. Cross-sectionally augmented Dickey Fuller test (CADF) is performed running the following regression (Pesaran, 2005: 18);

$$\Delta y_{i,t} = \rho_i y_{i,t-1} + c_i \bar{y}_{t-1} + \sum_{L=1}^{p_i} \theta_{i,L} \Delta y_{i,t-L} + \sum_{L=0}^{p_i} D_{i,L} \Delta\bar{y}_{t-L} + \alpha_{i,m} d_{m,t} + \varepsilon_{i,t}, \tag{6.75}$$

$d_{m,t}$ is defined as before and m=1, 2, 3. Individual CADF statistics ($t_i(N,T)$) are given by the OLS t-ratio of ρ_i in equation (6.75) (Pesaran, 2005: 18). Pesaran (2007) follows the Im, Pesaran and Shin (2003) approach and proposes cross-sectionally augmented IPS test (CIPS) given in equation (6.76) to test for panel unit root considering the null and alternative hypotheses given in (6.63);

$$CIPS(N,T) = N^{-1}\sum_{i=1}^{N} t_i(N,T) \tag{6.76}$$

Pesaran (2007) provides the simulated critical values for $t_i(N,T)$ and $CIPS(N,T)$ statistics for various combinations of N and T and deterministic term specifications. Pesaran, Smith and Yamagata (2009) propose a panel unit root test for multifactor error structure as an extension of Pesaran (2007)'s CADF and CIPS tests. They augment the ADF regression by the cross section averages of variable of interest but also the cross-sectional mean of additional regressors which are assumed to be affected by the same unobserved common factors as the variable of interest. Small samples performance of the test is shown to be well compared to the tests of Bai and Ng (2004) and Moon and Perron (2004).

Perron (1989) shows that usual ADF test statistics which do not account for the structural breaks in the series, are biased towards the nonrejection of a unit root, thus tests have very low power when there are structural breaks in time series data (Enders, 2004: 200; Harris and Sollis, 2003: 57). Carrion-i-Silvestre et al. (2005) develop a unit root test that considers the multiple structural breaks by extending the panel unit root test of Hadri (2000). They allow for different number of structural breaks at different dates for each cross section and also structural shift in the mean and/or trend of individual time series. They assume that data generating process for $y_{i,t}$ is given by the following expressions (Carrion-i-Silvestre et al., 2005: 160-161);

$$y_{i,t} = \alpha_{i,t} + \beta_i t + \varepsilon_{i,t} \tag{6.77}$$
$$\alpha_{i,t} = \alpha_{i,t-1} + \sum_{k=1}^{m_i} \theta_{i,k} D(T_{b,k}^i)_t + \sum_{k=1}^{m_i} \gamma_{i,k}\, DU_{i,k,t} + v_{i,t}$$

here, $v_{i,t} \sim iid(0, \sigma_{v,i}^2)$ and $\alpha_{i,0} = \alpha_i$; $i = 1,2,\dots,N$ and $t = 1,2,\dots,T$; $T_{b,k}^i$ shows the k[th] date of the break for i[th] cross section, $k = 1,2,\dots,m_i$; $m_i \geq 1$; $\{\varepsilon_{i,t}\}$ and $\{v_{i,t}\}$ are assumed to be mutually independent across i and t (Carrion-i-Silvestre et al., 2005: 161).

$$D(T_{b,k}^i)_t = \begin{cases} 1, & for \quad t = T_{b,k}^i + 1 \\ 0, & otherwise \end{cases};\ DU_{i,k,t} = \begin{cases} 1, & for \quad t > T_{b,k}^i \\ 0, & otherwise \end{cases} \tag{6.78}$$

Under null of stationarity which is $H_0 \colon \sigma_{v,i}^2 = 0$ for all $i = 1,2,\dots,N$; the model in equation (6.77) can be written as below which includes individual effects, individual structural break effects (shifts in the mean if $\beta_i \neq 0$) and temporal structural break effects (shifts in the individual time trend if $\gamma_{i,k} \neq 0$) (Carrion-i-Silvestre et al., 2005: 161);

$$y_{i,t} = \alpha_i + \beta_i t + \sum_{k=1}^{m_i} \theta_{i,k} DU_{i,k,t} + \sum_{k=1}^{m_i} \gamma_{i,k} DT_{i,k,t}^* + \varepsilon_{i,t} \tag{6.79}$$

where,

$$DT_{i,k,t}^* = \begin{cases} t - T_{b,k}^i, & for \quad t > T_{b,k}^i \\ 0, & otherwise \end{cases} \tag{6.80}$$

Test statistic that they propose allowing for heteroscedasticity of disturbances across cross sections is as follows;

$$LM(\lambda) = \frac{1}{N} \sum_{i=1}^{N} \left(\widehat{\omega}_i^{-2} T^{-2} \sum_{t=1}^{T} \hat{S}_{i,t}^2 \right) \tag{6.81}$$

where, $\hat{S}_{i,t}$ is the partial sum of OLS residuals obtained from the estimation of (6.79); $\widehat{\omega}_i^2$ is the consistent estimate of long-run variance of $\varepsilon_{i,t}$; λ_i shows the positions of breaks' dates as a fraction of T for each i. Under the assumption of long-run variance homogeneity across i, test statistic is given in (6.82) with $\widehat{\omega}^2 = \frac{1}{N} \sum_{i=1}^{N} (\widehat{\omega}_i^2)$;

$$LM(\lambda) = \frac{1}{N} \sum_{i=1}^{N} \left(\widehat{\omega}^{-2} T^{-2} \sum_{t=1}^{T} \hat{S}_{i,t}^2 \right) \tag{6.82}$$

Appropriate standardization of test statistic is shown to have standard normal limiting distribution as $(T, N \rightarrow \infty)_{seq}$. Estimation and testing of the breaks are performed following Bai and Perron (1998) procedure. To account for cross-sectional dependence, they suggest computing the bootstrap distribution of the statistic by the procedure described by Maddala and Wu (1999). Finite sample performance of the test is found to be well based on Monte Carlo simulations. In the next section, we discuss the panel cointegration testing procedures.

6.2.2. Panel Cointegration Tests

If linear combinations of integrated variables are stationary, then these variables are said to be cointegrated (Enders, 2004: 319). The concept of cointegration is first introduced by Engle and Granger (1987) in time series econometrics. In this context, Engle and Granger (1987), Phillips (1991), Kremers, Ericsson and Dolado (1992), Gregory and Hansen (1996) and Johansen (1991, 1995) develop various cointegration tests following different approaches such as residual-based, error correction-based and system-based approaches. As in the case of a single time series, panel cointegration tests are used to ensure that the statistical relationships between trending variables are not spurious (Cameron and Trivedi, 2009: 273). Harris and Sollis (2003) state that for cointegration tests using panel data, same beneficial effects should be observed as in panel unit root tests in terms of power improvement by pooling information across cross sections of a panel (Harris and Sollis, 2003: 21, 212). There are some important issues needed to be considered while testing for panel cointegration, such as unbalanced panels, cross section dependence, N and T asymptotic, heterogeneity in the parameters of cointegrating relationship, heterogeneity in the number of cointegrating relationships across cross sections and possibility of cointegration between the series from different cross sections (cross unit cointegration) that are pointed out by Verbeek (2004) and Breitung and Pesaran (2008). Panel cointegration tests can also be classified as residual-based, error correction-based and system-based cointegration tests like their time series counterparts. Depending on the assumption of cross-sectional independence, we have two groups that have already been defined in panel unit root tests, namely, first generation and second generation panel cointegration tests. In section 6.2.2.1, we give information on Pedroni (1999, 2004) and Kao (1999) residual-based and Larsson, Lyhagen and Löthgren (2001) likelihood-based tests; and in section 6.2.2.2, Westerlund (2006) residual-based LM and Westerlund (2007) error correction-based tests are reviewed.

6.2.2.1. First Generation Panel Cointegration Tests

Two groups of cointegration tests are proposed assuming that the cross section units are independent. The first group called residual-based tests are developed by Kao (1999) and Pedroni (1999, 2004) following Engle and Granger (1987) two-step cointegration test procedure in which residuals of panel static regression are used to construct the test statistics and tabulate the distributions (Barbieri, 2006: 4); and Larsson, Lyhagen and Löthgren (2001) suggest system-based test following the time series version proposed by Johansen (1991, 1995) employing heterogeneous Vector Autoregression model.

Kao (1999) proposes ADF and four DF-type unit root tests for the residuals of spurious regression in order to test for null hypothesis of no cointegration. He considers the following fixed effects model assuming $y_{i,t}$ and $x_{i,t}$ are I(1) and $w_{i,t}$ = $(u_{i,t}, e_{i,t})$ are independent across i;

$$y_{i,t} = \alpha_i + \beta x_{i,t} + \varepsilon_{i,t} \quad (6.83)$$
$$y_{i,t} = y_{i,t-1} + u_{i,t}$$
$$x_{i,t} = x_{i,t-1} + e_{i,t}$$

The estimate of covariance of $w_{i,t}$, let us call it $\hat{\Sigma}$, is obtained in an usual way as below;

$$\hat{\Sigma} = \begin{pmatrix} \hat{\sigma}_u^2 & \hat{\sigma}_{ue} \\ \hat{\sigma}_{ue} & \hat{\sigma}_e^2 \end{pmatrix} = \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{w}_{i,t}\, \hat{w}_{i,t}{}' \quad (6.84)$$

Ω is the long-run covariance matrix of $w_{i,t}$ and given by the following expression;

$$\Omega = \lim_{T\to\infty} \frac{1}{T} E\left(\sum_{t=1}^{T} w_{i,t}\right)\left(\sum_{t=1}^{T} w_{i,t}\right)' = \begin{pmatrix} \sigma_{0u}^2 & \sigma_{0ue} \\ \sigma_{0ue} & \sigma_{0e}^2 \end{pmatrix} \quad (6.85)$$

Ω is estimated using kernel estimator as follows where $\overline{\omega}_{\tau l}$ is a weight function or a kernel and l is a bandwidth parameter;

$$\widehat{\Omega} = \begin{pmatrix} \hat{\sigma}_{0u}^2 & \hat{\sigma}_{0ue} \\ \hat{\sigma}_{0ue} & \hat{\sigma}_{0e}^2 \end{pmatrix} \tag{6.86}$$

$$= \frac{1}{N}\sum_{i=1}^{N}\left\{\frac{1}{T}\sum_{t=1}^{T}\widehat{w}_{i,t}\widehat{w}_{i,t}{}' + \frac{1}{T}\sum_{\tau=1}^{l}\overline{\omega}_{\tau l}\sum_{t=\tau+1}^{T}(\widehat{w}_{i,t}\widehat{w}'_{i,t-\tau} + \widehat{w}_{i,t-\tau}\widehat{w}'_{i,t})\right\}$$

In order to test for null of no cointegration, following pooled regression is run using the within residuals of (6.83) and the null hypothesis to be tested becomes $H_0\colon \rho = 1$;

$$\hat{\varepsilon}_{i,t} = \rho\hat{\varepsilon}_{i,t-1} + \textstyle\sum_{j=1}^{p}\gamma_j\,\Delta\hat{\varepsilon}_{i,t-j} + v_{i,t} \tag{6.87}$$

For DF-type test, we set $\gamma_j = 0$ for all j=1,...,p in equation (6.87) and for this case, OLS estimate of ρ and t-statistic are given below;

$$\widehat{\rho} = \frac{\sum_{i=1}^{N}\sum_{t=2}^{T}\hat{\varepsilon}_{i,t}\ \hat{\varepsilon}_{i,t-1}}{\sum_{i=1}^{N}\sum_{t=2}^{T}\hat{\varepsilon}_{i,t-1}^2} \tag{6.88}$$

$$t_\rho = \frac{(\widehat{\rho}-1)\sqrt{\sum_{i=1}^{N}\sum_{t=2}^{T}\hat{\varepsilon}_{i,t-1}^2}}{\sqrt{\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=2}^{T}(\hat{\varepsilon}_{i,t} - \widehat{\rho}\hat{\varepsilon}_{i,t-1})^2}} \tag{6.89}$$

Following DF-type tests are proposed by Kao (1999) given $\widehat{\rho}, t_\rho, \widehat{\Sigma}$ and $\widehat{\Omega}$;

$$DF_\rho = \frac{\sqrt{N}T(\widehat{\rho}-1)+3\sqrt{N}}{\sqrt{10.2}} \tag{6.90}$$

$$DF_t = \sqrt{1.25}t_\rho + \sqrt{1.875N} \tag{6.91}$$

$$DF_\rho^* = \frac{\sqrt{N}T(\widehat{\rho}-1)+(\frac{3\sqrt{N}\hat{\sigma}_v^2}{\hat{\sigma}_{0v}^2})}{\sqrt{3+\frac{36\hat{\sigma}_v^4}{5\hat{\sigma}_{0v}^4}}} \tag{6.92}$$

$$DF_t^* = \frac{t_\rho + (\frac{\sqrt{6N}\hat{\sigma}_v}{2\hat{\sigma}_{0v}})}{\sqrt{\frac{\hat{\sigma}_{0v}^2}{2\hat{\sigma}_v^2} + \frac{3\hat{\sigma}_v^2}{10\hat{\sigma}_{0v}^2}}} \tag{6.93}$$

DF_ρ and DF_t called bias-corrected statistics are constructed under the assumption of no autocorrelation and strong exogeneity of the regressors and errors (Barbieri, 2006: 8). DF_ρ^* and DF_t^* test statistics are designed to allow for endogeneity between regressors and errors. $\hat{\sigma}_v^2$ and $\hat{\sigma}_{0v}^2$ in expressions (6.92) and (6.93) are calculated as;

$$\hat{\sigma}_v^2 = \hat{\sigma}_u^2 \text{-} \hat{\sigma}_{ue}^2 \hat{\sigma}_e^{-2} \text{ and } \hat{\sigma}_{0v}^2 = \hat{\sigma}_{0u}^2 \text{-} \hat{\sigma}_{0ue}^2 \hat{\sigma}_{0e}^{-2} \tag{6.94}$$

For p>0 in equation (6.87), he develops ADF-type statistic. Let us define E_{ip} as a matrix of observations on p regressors $(\Delta\hat{\varepsilon}_{i,t-1}, \dots, \Delta\hat{\varepsilon}_{i,t-p})$; $Q_i = I - E_{ip}(E_{ip}{}' E_{ip})^{-1} E_{ip}{}'$; ε_i as a vector of observations on $\hat{\varepsilon}_{i,t-1}$; v_i is a vector of observations on v_{it} and $s_v^2 = \left(\frac{1}{NT}\right) \sum_{i=1}^N \sum_{t=1}^T \hat{v}_{i,t}^2$. $\hat{\rho}$ is the OLS estimate of ρ. The expression for t_{ADF} statistic is given in (6.96) where $\hat{\rho} - 1$ is defined in equation (6.95).

$$\hat{\rho} - 1 = \left(\sum_{i=1}^N \varepsilon_i{}' Q_i \varepsilon_i\right)^{-1} \left(\sum_{i=1}^N \varepsilon_i{}' Q_i v_i\right) \tag{6.95}$$

$$t_{ADF} = \frac{(\hat{\rho} - 1)\sqrt{\sum_{i=1}^N \varepsilon_i{}' Q_i \varepsilon_i}}{s_v} \tag{6.96}$$

Then, under null hypothesis of no cointegration Kao (1999) suggests to use the following ADF-type statistic which does not depend on nuisance parameters and can be considered as an augmented version of DF_t^*;

$$ADF = \frac{t_{ADF} + (\frac{\sqrt{6N}\hat{\sigma}_v}{2\hat{\sigma}_{0v}})}{\sqrt{\frac{\hat{\sigma}_{0v}^2}{2\hat{\sigma}_v^2} + \frac{3\hat{\sigma}_v^2}{10\hat{\sigma}_{0v}^2}}} \tag{6.97}$$

All these DF-type and ADF-type test statistics are shown to have standard normal N(0, 1) limiting distributions as $(T, N \to \infty)_{seq}$, thus, their asymptotic distributions are independent of nuisance parameters.

Pedroni (1999, 2004) residual-based tests allow for short-run and long-run heterogeneity across cross sections besides the endogeneity of regressors. He considers the following model with individual fixed effects, individual time trends and heterogeneous slope coefficients assuming that $y_{i,t}$ and $x_{j,i,t}$ are I(1) and also $x_{j,i,t}$'s are not cointegrated;

$$y_{it} = \alpha_i + \delta_i t + \sum_{j=1}^{M} \beta_{j,i}\, x_{j,i,t} + \varepsilon_{it};\, i = 1, \dots, N;\, t = 1, \dots, T;\, m = 1, \dots, M \quad (6.98)$$

In order to test the null hypothesis of no cointegration, the following auxiliary regression is performed using the residuals obtained from (6.98);

$$\hat{\varepsilon}_{i,t} = \rho_i \hat{\varepsilon}_{i,t-1} + \sum_{j=1}^{p_i} \gamma_j\, \Delta\hat{\varepsilon}_{i,t-j} + v_{i,t} \quad (6.99)$$

The null hypothesis $H_0\colon \rho_i = 1$ is tested against homogeneous (6.100) and heterogeneous (6.101) alternatives to construct within dimension (panel) statistics test and between dimension (group) statistics test, respectively.

$$H_1{}^P\colon \rho_i = \rho < 1\; for\; all\; i \quad (6.100)$$
$$H_1{}^G\colon \rho_i < 1\; for\; all\; i \quad (6.101)$$

Autocorrelation correction is based on either nonparametric approach by setting p_i=0 for all i in equation (6.99) or parametric approach taking p_i>0 in equation (6.99). He develops four within dimension (panel) statistics which are nonparametric variance ratio statistic (panel v), nonparametric test statistic analogous to Phillips and Perron (1988) rho-statistic (panel rho), nonparametric test statistic analogous to Phillips and Perron (1988) t-statistic (nonparametric panel t), parametric test similar to ADF-type test (parametric panel t); on the other hand, three between dimension versions of last three (group) statistics, namely group rho, nonparametric group t and parametric group t statistics are constructed. Detailed information on the test statistics are given in Table 1 of Pedroni (1999). The panel statistics require the estimation of individual long run conditional variance for the residuals. This can be obtained by calculating the long run variance of residuals from the differenced regression in equation (6.102) employing any kernel estimator.

$$\Delta y_{it} = \sum_{j=1}^{M} b_{j,i}\, \Delta x_{j,i,t} + \eta_{it}; \tag{6.102}$$

All seven statistics are standardized with respect to N and T dimensions and adjusted by using mean and variance adjustment terms generated by Monte Carlo simulations and presented in Table 2 of Pedroni (1999) for each statistics, number of regressors and deterministic terms specification. Pedroni (1999) shows that standardized and adjusted statistics are asymptotically distributed as N(0, 1).

Different from the above two tests, in a multivariate framework allowing for multiple cointegration relation, Larsson, Lyhagen and Löthgren (2001) develop a likelihood-based panel cointegration test for the existence of a common cointegrating rank in the heterogeneous panels taking the average of individual rank trace statistics proposed by Johansen (1988, 1991, 1995) (Harris and Sollis, 2003: 204; Breitung and Pesaran, 2008: 309). Following heterogeneous VAR (k_i) model without any deterministic term, is considered in their study;

$$Y_{i,t} = \sum_{k=1}^{k_i} \Pi_{\mathrm{i,k}}\, Y_{i,t-k} + \varepsilon_{i,t}, i = 1, \dots, N \text{ and } t = 1, \dots, T \tag{6.103}$$

where, $Y_{i,t} = (y_{i,1,t}, \dots, y_{i,p,t})'$ for each i at time period t assuming there are $j = 1, \dots, p$ variables in each cross-section. The values of $\{Y_{i,t-k}\}_{k=1}^{k_i}$ at t=1 are assumed to be fixed and $\varepsilon_{i,t} \sim iidN_p(0, \Omega_\mathrm{i})$. The heterogeneous error correction representation of VAR model in (6.103) is as follows (Larsson, Lyhagen and Löthgren, 2001: 111);

$$\Delta Y_{i,t} = \Pi_{\mathrm{i}} Y_{i,t-1} + \sum_{k=1}^{k_i-1} \Gamma_{\mathrm{i,k}} \Delta Y_{i,t-k} + \varepsilon_{i,t}, i = 1, \dots, N \tag{6.104}$$

here, Π_{i} is $\mathrm{p} \times \mathrm{p}$ and is of reduced rank. The model (6.104) is estimated for each i, separately. The hypothesis testing on the cointegrating rank is performed by considering following null and alternative hypotheses (Larsson, Lyhagen and Löthgren, 2001: 111-112);

$$H_0(r): rank(\Pi_{\mathrm{i}}) = \mathrm{r_i} \leq \mathrm{r} \text{ for all } i = 1, \dots, N \tag{6.105}$$

$$H_1(p): rank(\Pi_{\mathrm{i}}) = p \text{ for all } i = 1, \dots, N \tag{6.106}$$

The trace statistic for cross section i is based on $\hat{\lambda}_{im}$, m$^{\text{th}}$ eigenvalue of a eigenvalue problem;

$$LR_{iT} = -T \sum_{m=r+1}^{p} \ln(1 - \hat{\lambda}_{im}) \tag{6.107}$$

They construct the panel cointegration test by calculating the mean of the individual rank trace statistics (Larsson, Lyhagen and Löthgren, 2001: 109);

$$\overline{LR}_{NT} = \frac{1}{N} \sum_{i=1}^{N} LR_{iT} \tag{6.108}$$

They show that standardized LR-bar statistic is asymptotically standard normal distributed as N and T$\rightarrow \infty$ such that $\sqrt{N}T^{-1} \rightarrow 0$ by assuming homogeneous long run dynamics and heterogeneous short run dynamics among cross sections. The mean and variance of asymptotic trace statistic used for the standardization is simulated and tabulated in Table 1 in their study by Larsson, Lyhagen and Löthgren (2001). The sequential testing procedure of Johansen (1988) is suggested to be implemented. Up to here, these tests do not allow for dependency between the cross sections. In the next section, we continue with the panel cointegration tests that consider this issue.

6.2.2.2. Second Generation Panel Cointegration Tests

In this section, we review Westerlund (2006) residual-based LM and Westerlund (2007) error correction-based panel cointegration tests. Westerlund (2006) residual-based LM test is an extension of residual-based LM test proposed by McCoskey and Kao (1998) in which null hypothesis of cointegration is tested against the alternative of no cointegration based on the univariate LM cointegration tests developed by Harris and Inder (1994) and Shin (1994). As ignorance of structural breaks in the series can cause misleading results for the panel cointegration tests, Westerlund (2006) allows for multiple structural breaks in the level and trend of the cointegrated panel regression with unknown number and different dates for each cross section. He proposes test statistics for three cases as when there are no breaks, break dates are known; and dates are unknown and determined from the data.

For the case where the dates of breaks are known, he considers the following model for $y_{i,t}$ where, d_{it} is a vector of deterministic terms; x_{it} is a K-dimensional vector of regressors; there are known M_i breaks located at the known dates $T_{i1}, \dots, T_{iM_i}$ indexed by $j = 1, \dots, M_i$ and $T_{ij} = [\lambda_{ij} T]$ such that $\lambda_{ij} \in (0,1)$ and $\lambda_{ij-1} < \lambda_{ij}$, i.e., locations of breaks are constant fraction of T;

$$y_{i,t} = d'_{it}\,\gamma_{ij} + x'_{it}\beta_i + e_{i,t} \qquad (6.109)$$

$$e_{i,t} = r_{i,t-1} + u_{i,t}$$

$$r_{i,t} = r_{i,t-1} + \phi_i u_{i,t}$$

$$x_{i,t} = x_{i,t-1} + v_{i,t}$$

The cointegration within the regressors is not allowed but regressors may be endogenous. The autocorrelation properties are also considered. The test statistic and its asymptotic distribution are derived under the assumption that the vector, $w_{i,t} = (u_{i,t}, v_{i,t}{}')'$ is cross-sectionally independent. He suggests using bootstrap approach for the problem of cross sectional dependence. Under this setting, test statistic is constructed for five cases in which cointegrated regression includes no deterministic component; only individual specific intercept; individual specific intercept and trend; at least one break in the level for at least one individual; at least one break in the level and trend for at least one individual. The expressions (6.110) and (6.111) give null hypothesis of cointegration against the alternative hypothesis, respectively;

$$H_0: \phi_i = 0 \; for \; all \; i = 1, \ldots, N \tag{6.110}$$

against

$$H_1: \begin{cases} \phi_i \neq 0 & for \quad i = 1,2,3, \ldots, N_1 \\ \phi_i = 0 & for \quad i = N_1 + 1, \ldots, N \end{cases} \quad \text{such that} \tag{6.111}$$

$$lim_{N\to\infty}\left({}^{N_1}\!/_{N}\right) = \delta \; where \; 0 < \delta \leq 1.$$

Given the long-run covariance matrix of $w_{i,t}$ in (6.112) which can be estimated using any semiparametrical kernel estimator using OLS estimate of e_{it}, long-run covariance of $u_{i,t}$ conditional on $v_{i,t}$ in (6.113) and defining $S_{i,t} = \sum_{k=T_{ij-1}+1}^{t} \hat{e}_{i,k}^{*}$, here $\hat{e}_{ik}^{*}$ is an efficient estimate of e_{it} obtained by employing DOLS or FMOLS estimator; Westerlund (2006) develops the panel LM test statistic, Z(M) in (6.114) in which $M = M_1, \ldots, M_N$.

$$\Omega_{\mathrm{i}} = \begin{pmatrix} \omega_{i11}^2 & \omega_{i21}' \\ \omega_{i21} & \Omega_{\mathrm{i}22} \end{pmatrix} \tag{6.112}$$

$$\omega_{i1.2}^2 = \omega_{i11}^2 - \omega_{i21}' \Omega_{\mathrm{i}22}{}^{-1} \omega_{i21} \tag{6.113}$$

$$Z(M) = \sum_{i=1}^{N} \sum_{j=1}^{M_i+1} \sum_{t=T_{ij-1}+1}^{T_{ij}} (T_{ij} - T_{ij-1})^{-2} \, \widehat{\omega}_{i1.2}^{-2} S_{i,t}{}^2 \tag{6.114}$$

We should be aware of that the statistic is a function of number of breaks for each cross section and thus, its asymptotic distribution depends also on M. When the dates of breaks are unknown, he suggests to follow the iterative procedure described by

Bai and Perron (1998, 2003). In this case, as the dates are determined endogenously from the data, the test statistic takes the following form by replacing T_i with $\hat{T}_i$;

$$Z(M) = \sum_{i=1}^{N} \sum_{j=1}^{\hat{M}_i+1} \sum_{t=\hat{T}_{ij-1}+1}^{\hat{T}_{ij}} (\hat{T}_{ij} - \hat{T}_{ij-1})^{-2}\, \hat{\omega}_{i1.2}^{-2} {S_{i,t}}^{2} \tag{6.115}$$

Asymptotic distribution of the standardized test statistic is shown to be standard normal distribution under null of cointegration as $(T, N \to \infty)_{seq}$ independent of autocorrelation properties and dates of breaks. The standardization of the statistic is described in Westerlund (2005). In order to standardize the statistic, simulated values for asymptotic mean and variance of the statistics are given in Table 1 of Westerlund (2005) for each deterministic term specification and number of regressors.

Westerlund (2007) proposes an alternative panel cointegration test to residual-based tests, based on error correction model. As shown by Banerjee, Dolado and Mestre (1998) and Kremers, Ericsson and Dolado (1992), the invalid common factor restriction in residual-based tests can lead to severe power loss (Persyn and Westerlund, 2008: 232). He develops two group mean statistics and two panel statistics in order to test for null of no cointegration against two distinct alternatives such that under one of them at least one cross section is cointegrated allowing for heterogeneity and under the other one, panel is cointegrated as a whole assuming homogeneous long-run relation among the cross sections, respectively. He considers cross-sectional dependence by a bootstrap procedure and in addition, tests allow for heterogeneous short run and long run dynamics, such as heterogeneous autocorrelation structure among cross sections, individual specific intercepts, trend terms and slope coefficients and weakly exogenous regressors. To construct test statistics, following conditional error correction model is considered (Persyn and Westerlund, 2008: 233);

$$\Delta y_{i,t} = \delta_{i,m}' d_{mt} + \alpha_i (y_{i,t-1} - \beta_i' x_{i,t-1}) + \sum_{j=1}^{p_i} \alpha_{ij}\, \Delta y_{i,t-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij}\, \Delta x_{i,t-j} + e_{it} \tag{6.116}$$

where, m=1, 2, 3; d_{mt} is the vector of deterministic components with m=1 if there is no any deterministic term, m=2 if there is only individual effects, m=3 if there is both individual effects and time trends; $x_{i,t} = x_{i,t-1} + v_{i,t}$ is a pure random walk and $x_{i,t}$'s are not cointegrated and error correcting. The reparametrization of (6.116) is given by;

$$\Delta y_{i,t} = \delta'_{i,m} d_{mt} + \alpha_i y_{i,t-1} + \lambda'_i x_{i,t-1} + \sum_{j=1}^{p_i} \alpha_{ij} \, \Delta y_{i,t-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij} \, \Delta x_{i,t-j} + e_{it} \quad (6.117)$$

In the above error correction model, we need $\alpha_i < 0$ for the evidence of error correction and thus, cointegration between $y_{i,t}$ and $x_{i,t}$. $\alpha_i = 0$ means that there exists no error correction and therefore, no cointegration. With this reasoning, the null and alternative hypothesis are given in (6.118), (6.119) and (6.119');

$$H_0: \alpha_i = 0 \; for \; all \; i \quad (6.118)$$

$$H_1{}^P: \alpha_i = \alpha < 0 \; for \; all \; i \quad (6.119)$$

$$H_1{}^G: \alpha_i < 0 \; for \; at \; least \; some \; i \quad (6.119')$$

The test statistics are constructed using the least square estimate of α_i ($\hat{\alpha}_i$) and its associated t-ratio. The constructions of group mean statistics involve three steps. In the first step, equation (6.115) is estimated for each i using least squares. Then, estimation of $\alpha_i = 1 - \sum_{j=1}^{p_i} \alpha_{ij}$ is performed using either parametric or semiparametric kernel estimation in the second step. Third step involves the computation of test statistics as in (6.120) where SE($\hat{\alpha}_i$) is the standard error of $\hat{\alpha}_i$ and in (6.121).

$$G_\tau = \frac{1}{N} \sum_{i=1}^{N} \frac{\hat{\alpha}_i}{\mathrm{SE}(\hat{\alpha}_i)} \quad (6.120)$$

$$G_\alpha = \frac{1}{N} \sum_{i=1}^{N} \frac{T\hat{\alpha}_i}{\hat{\alpha}_i(1)} \quad (6.121)$$

Panel statistics are also constructed in three steps. In the first step, individual lag orders are determined for each i and then regressions of $\Delta y_{i,t}$ and $y_{i,t-1}$ on $(d_{mt}, \{\Delta y_{i,t-j}\}_{j=1}^{p_i}, \{\Delta x_{i,t-j}\}_{j=-q_i}^{p_i}$) are performed to obtain the following residuals in (6.122) and (6.123);

$$\Delta\tilde{y}_{i,t} = \Delta y_{i,t} - \hat{\delta}_{i,m}' d_{mt} - \hat{\lambda}_i' x_{i,t-1} + \sum_{j=1}^{p_i} \hat{\alpha}_{ij}\, \Delta y_{i,t-j} - \sum_{j=-q_i}^{p_i} \hat{\gamma}_{ij}\, \Delta x_{i,t-j} \qquad (6.122)$$

$$\tilde{y}_{i,t-1} = y_{i,t-1} - \tilde{\delta}_{i,m}' d_{mt} - \tilde{\lambda}_i' x_{i,t-1} - \sum_{j=1}^{p_i} \tilde{\alpha}_{ij}\, \Delta y_{i,t-j} - \sum_{j=-q_i}^{p_i} \tilde{\gamma}_{ij}\, \Delta x_{i,t-j} \qquad (6.123)$$

The second step involves the computation of $\hat{\alpha}$ and SE($\hat{\alpha}$) as in (6.124) and (6.125).

$$\hat{\alpha} = \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \tilde{y}_{it}^2\right)^{-1} \sum_{i=1}^{N} \sum_{t=2}^{T} \frac{1}{\hat{\alpha}_i(1)} \tilde{y}_{it-1}\, \Delta\tilde{y}_{i,t} \qquad (6.124)$$

$$\mathrm{SE}(\hat{\alpha}) = \left(\left(\hat{S}_N^2\right)^{-1} \sum_{i=1}^{N} \sum_{t=2}^{T} \tilde{y}_{it-1}^2\right)^{-1/2} \qquad (6.125)$$

where, $\hat{S}_N^2 = \frac{1}{N}\sum_{i=1}^{N} \hat{S}_i^2$ in which $\hat{S}_i$ is the consistent estimate of conditional long-run standard deviation of $\Delta y_{i,t}$ conditioned on current, lagged and lead values of $\Delta x_{i,t}$. In the last step, the panel statistics are computed as in (6.126) and (6.127).

$$P_\tau = \frac{\hat{\alpha}}{\mathrm{SE}(\hat{\alpha})} \qquad (6.126)$$

$$P_\alpha = T\hat{\alpha} \qquad (6.127)$$

All the test statistics after being normalized and standardized by a function of N and suitable moments, respectively, are shown to have asymptotic null standard normal distributions as $(T, N \to \infty)_{seq}$. Westerlund (2007) simulates the asymptotic moments for each deterministic term specification and different number of regressors and presents them in Table 1 of his paper. After briefly explaining the methods that are employed in the applications, in sections 7 and 8, the results of our empirical applications are presented.

CHAPTER 7

PANEL DATA APPLICATION TO TURKEY

In this section, we apply our electricity consumption model to provinces of Turkey. Information on data used in the analysis and its sources are given in section 7.1. In section 7.2, we estimate the static models by pooled OLS and within estimation and give results of diagnostic tests for each estimation with different volatility variable. We extend our model by including dynamics in section 7.3 and present the estimation results of dynamic panel data model for several estimation methods.

7.1. Data

We employ annual balanced panel data on 65 provinces of Turkey between the years 1990 and 2001. The start and end periods of the data set were constrained by the availability of the data on provincial GDP after 2001 and data on sectoral electricity consumption before 1990. Data set consists of per capita electricity consumption (pcec), per capita gross domestic product (pcgdp), electricity end-use prices (rep), urbanization ratio (uratio), heating degree days (hdd), cooling degree days (cdd), conditional variance of growth of real exchange rate calculated using PPI (h1_reexp), conditional variance of growth of real exchange rate calculated using CPI (h2_reexc), conditional variance of industrial production index growth (h3_ipi), conditional variance of crude oil price growth (h4_poil), conditional variance of nominal exchange rate growth (h5_nexcr) and conditional variance of İstanbul Stock Exchange-100 index growth (h6_ise100). Data for total electricity consumption (kWh), sectoral electricity consumption (kWh) and sectoral electricity end-use prices (TL/kWh) are taken from Turkish Electricity Distribution Company (Co. Inc.). Population, GDP and urban population data of provinces are from TURKSTAT Database. Average daily temperatures for each provinces are obtained from Turkish

State Meteorological Service for calculation of hdd and cdd variables. İstanbul Chamber of Commerce (İTO) wholesale price index (general, 1968=100) used for deflation of GDP and electricity end-use prices is taken from Electronic Data Delivery System of CBRT. Calculations of conditional variances of growth of real exchange rate calculated using PPI, growth of real exchange rate calculated using CPI, industrial production index growth, crude oil price growth, nominal exchange rate growth and İstanbul Stock Exchange-100 index growth are given in Section 5.

Some arrangements are made in the data before analysis. Gaps in the total population and urban population data are interpolated using exponential function method following Kocaman (2002). As after 1989, new provinces have emerged due to the province status gained by some towns, we rearrange the data on total population, urban population, total and sectoral electricity consumption and GDP in such a way that data values on new provinces are added to the provinces that they were disjoined according to the information obtained from the website of Ministry of Justice. Electricity end-use price is calculated by taking the weighted average of sectoral electricity end-use prices using the electricity consumption share of each sector out of total electricity consumption as weights. Urbanization ratio is obtained by dividing urban population to the total population of each province. Populations of each province over the period are used to obtain per capita values. Heating degree days and cooling degree days are calculated by the method described by Turkish State Meteorological Service. Calculations for each day and province are based on the following formulae (Şensoy and Ulupınar, 2008);

$$HDD_i = \begin{cases} (18°\mathrm{C} - T_{mi}) & if\ T_{mi} \leq 15 \\ 0 & if\ T_{mi} > 15 \end{cases}, \quad \text{i=1,...,365.} \tag{7.1}$$

$$CDD_i = \begin{cases} (T_{mi} - 22°\mathrm{C}) & if\ T_{mi} > 22 \\ 0 & if\ T_{mi} \leq 22 \end{cases}, \quad \text{i=1,...,365.}$$

where, T_{mi} is the average daily temperature.

We sum the daily CDD_i and HDD_i values to obtain annual values (hdd and cdd). The data on per capita electricity consumption, per capita real gross domestic product and real electricity end use price series are transformed using natural logarithm. Table 7.1 presents the descriptive statistics.

We infer that h1_reexp, h2_reexc, h3_ipi, h4_poil, h5_nexcr and h6_ise100 variables are province invariant as their between standard deviations are zero. Uratio variable has small within standard deviation which is a sign that within estimation can produce poor results related to its coefficient compared with the others. Tremendous loss in efficiency can be brought about in within estimation as between variation is larger than the within for most of the variables with the exceptions such as h1_reexp, h2_reexc, h3_ipi, h4_poil, h5_nexcr and h6_ise100 variables.

Pairwise correlations for all the variables are presented in Table 7.2. High and positive correlation is observed between lnpcec and lnpcgdp. Other pairwise correlations of lnpcec are less than 0.5 and signs of some correlations are contrary to our expectations such as the ones with lnrep, hdd, h1_reexp, h3_ipi, h4_poil, h5_nexcr and h6_ise100. Negative correlation between hdd and lnpcec may show us that electricity is not used so much for heating purposes and even, when heating needs increase, people consume less electricity. Other pairwise correlations among the explanatory variables those are smaller than 0.5 show that there is no evidence of high collinearity among them.

In Figures A.5-A.11, time series graphs are presented for each variable and each province. For lnpcec series, in some provinces increasing trend and for others cyclical pattern are observed. lnpcgdp series show cyclical pattern and sharp decreases in 1994 and 2001 as a result of crises in these years. But for Kahramanmaraş, we observe increasing trend in lnpcgdp series and crises seem to have no effect on the economy for this province. As electricity prices are regulated by the government, lnrep has same cyclical pattern across the provinces. uratio increases in almost all the provinces over time except Hatay, İçel, İstanbul and Kocaeli in which we observe decreasing trend.

Although hdd has a cyclical pattern around a constant value, in cdd, we observe a cyclical pattern around a increasing trend showing us that the summers tend to become much hotter increasing cooling needs.

Table 7.1 Summary Statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
pcec	overall	975.2709	861.6448	97.49	7102.42	N=780
	between		790.9012	164.4058	4377.873	n=65
	within		354.5982	-1018.98	3699.818	T=12
pcgdp	overall	103.2815	52.51895	23.5	373.21	N=780
	between		49.95565	29.5225	328.885	n=65
	within		17.26014	17.89897	235.039	T=12
rep	overall	0.003197	0.000432	0.002126	0.004439	N=780
	between		5.43E-05	0.002988	0.003326	n=65
	within		0.000429	0.002162	0.004407	T=12
uratio	overall	0.521487	0.121312	0.27	0.92	N=780
	between		0.118381	0.310833	0.910833	n=65
	within		0.030007	0.418154	0.628154	T=12
hdd	overall	2390.004	877.007	526.4	5671.1	N=780
	between		848.3005	757.6583	4852.217	n=65
	within		244.3132	1518.154	3444.388	T=12
cdd	overall	260.0574	246.6466	0.3	1165.8	N=780
	between		240.994	5.658333	1033.4	n=65
	within		59.80418	65.64077	450.8408	T=12
lnpcec	overall	6.595369	0.757331	4.57975	8.868191	N=780
	between		0.715726	5.040345	8.294726	n=65
	within		0.261762	5.807487	7.329725	T=12
lnpcgdp	overall	4.51865	0.493763	3.157	5.922141	N=780
	between		0.470469	3.36499	5.791121	n=65
	within		0.159957	3.964092	5.209798	T=12

(Table 7.1. Continued)

Variable		Mean	Std. Dev.	Min	Max	Observations
lnrep	overall	-5.75458	0.133309	-6.15367	-5.41734	N=780
	between		0.017696	-5.82204	-5.71455	n=65
	within		0.132146	-6.13709	-5.42408	T=12
h1_reexp	overall	0.001217	0.001539	0.000375	0.005229	N=780
	between		0	0.001217	0.001217	n=65
	within		0.001539	0.000375	0.005229	T=12
h2_reexc	overall	0.000488	0.000135	0.000272	0.000719	N=780
	between		0	0.000488	0.000488	n=65
	within		0.000135	0.000272	0.000719	T=12
h3_ipi	overall	0.001021	0.00029	0.000532	0.001518	N=780
	between		0	0.001021	0.001021	n=65
	within		0.00029	0.000532	0.001518	T=12
h4_poil	overall	0.007736	0.00275	0.004173	0.012442	N=780
	between		0	0.007736	0.007736	n=65
	within		0.00275	0.004173	0.012442	T=12
h5_nexcr	overall	0.000195	0.000302	2.26E-05	0.00102	N=780
	between		0	0.000195	0.000195	n=65
	within		0.000302	2.26E-05	0.00102	T=12
h6_ise100	overall	0.016183	0.008438	0.009979	0.041315	N=780
	between		0	0.016183	0.016183	n=65
	within		0.008438	0.009979	0.041315	T=12

Notes: lnpcec=ln(pcec), lnpcgdp=ln(pcgdp), lnrep=ln(rep), Variation over time (across provinces) is defined by within (between) variation. Overall variance is decomposed as within and between variance. Minimum and maximum of panel series are given by columns min and max for overall (x_{it}), between ($\bar{x}_i$) and within ($x_{it} - \bar{x}_i + \bar{x}$). N is the total number of observations, n shows the number of provinces. T is the time series dimension for each province.

For the volatility variables, in 2001 as a result of economic crisis in Turkey, we observe that some of the series reach their peak values. Other peaks in h1_reexp, h2_reexc and h5_nexcr series for the years 1994 and 1995 can be explained by 1994 crisis effect. Besides, increase in h6_ise100 series for year 1991 can be due to Gulf crisis between 1990 and 1991. Lastly, Henriques and Sadorsky (2011) discuss that the peaks of 1999 and 2001 in oil price volatility series (h4_poil) can be related to the concerns about year 2000 problem (millennium bug) in 1999 and September 11, 2001 Terrorist attack on World Trade Centre in New York.

Table 7.2 Correlation Matrix

Variable	lnpcec	lnpcgdp	lnrep	uratio	hdd	cdd	h1_reexp	h2_reexc	h3_ipi	h4_poil	h5_nexcr	h6_ise100
lnpcec	1.00											
lnpcgdp	0.87	1.00										
lnrep	0.27	0.23	1.00									
uratio	0.49	0.49	0.20	1.00								
hdd	-0.52	-0.55	-0.12	-0.30	1.00							
cdd	0.18	0.14	0.12	0.27	-0.63	1.00						
h1_reexp	0.02	-0.05	0.43	0.03	-0.08	0.09	1.00					
h2_reexc	-0.22	-0.23	-0.39	-0.14	0.05	-0.07	0.23	1.00				
h3_ipi	0.23	0.16	0.61	0.17	-0.09	0.09	0.15	-0.34	1.00			
h4_poil	0.16	0.13	0.35	0.12	-0.14	0.12	0.04	-0.27	0.46	1.00		
h5_nexcr	0.08	-0.003	0.55	0.07	-0.11	0.10	0.90	0.27	0.34	0.25	1.00	
h6_ ise100	0.14	0.09	0.59	0.12	-0.09	0.12	0.39	0.06	0.53	0.72	0.67	1.00

7.2. Estimation Results of Pooled and Fixed Effects Models

In sections 7.2.1, 7.2.2, 7.2.3, 7.2.4, 7.2.5 and 7.2.6, we present the estimation and diagnostic test results of pooled and fixed effects models employing different volatility variables.

7.2.1. Estimation Results for the Pooled and Fixed Effects Model with h1_reexp

First we estimate pooled model in which all the coefficients are assumed to be same across provinces and years. Then, we relax this assumption and allow heterogeneity assuming only the intercept in the model vary across cross-sections with a fixed effects model. As sample is not generated by using a random sampling process and it is formed in the context of predefined definitions, we will assume the effects in our model if exist, are fixed. Estimation and diagnostic test results are given in Table 7.3.

From estimation results, we observe that signs of coefficients on some variables, such as coefficients on lnrep in all estimations, hdd in all except FGLSDV estimation, cdd in only pooled FGLS, h1_reexp in all except fixed effects within estimation, are contrary to the theoretical expectations. However, in most of the estimations, these coefficients excluding the one on h1_reexp variable are statistically insignificant. Coefficients on lnpcgdp and uratio are highly significant and have correct sign. Diagnostic test results for pooled OLS model estimation indicate presence of autocorrelation and heteroscedasticity in the residuals. We perform FGLS estimation under the assumption of common AR(1) coefficients for all provinces estimated as 0.7768 to consider autocorrelation and heteroscedasticity in the pooled model. Heteroscedasticity and autocorrelation problems can be due to omission of important variables from the model and/or disregarded heterogeneity in the data. We handle heterogeneity and unobservable qualitative factors in the context of one way fixed effects model.

First, we need to test for the individual effects under the assumption of no time effects; $H_0 : \mu = 0 \mid \lambda = 0$ *vs.* $H_1 : \mu \neq 0 \mid \lambda = 0$. F statistic and associated p-value are 72.40129 and 0.000, respectively. We find that individual effects are significant. But in the residuals of this estimation, in addition to autocorrelation and heteroscedasticity, problem of cross-sectional dependence exist. To overcome consequences of cross-sectional dependence and assuming cross-sectional dependence are due to the common factors that are uncorrelated with regressors, we employ Driscoll and Kraay (1998) standard errors for the calculation of t ratios.

Table 7.3 Pooled and Fixed Effects Estimations of Electricity Consumption Model with h1_reexp

Dependent variable: lnpcec	**Pooled OLS**	**Pooled FGLS**	**Fixed Effects (within)**	**FGLSDV estimation**
lnpcgdp	1.241293*** (0.000)	0.9480456*** (0.000)	0.469036*** (0.000)	0.49972*** (0.000)
lnrep	0.3046957 (0.213)	0.0034336 (0.930)	0.2436326 (0.150)	0.0606027** (0.039)
uratio	0.3575064*** (0.000)	1.341438*** (0.000)	4.254791*** (0.000)	5.12248*** (0.000)
hdd	-0.0000335 (0.150)	-6.48E-06 (0.654)	-0.0000363 (0.287)	0.0000253* (0.053)
cdd	0.0000606 (0.567)	-0.0000499 (0.354)	0.0004564* (0.079)	0.0001346** (0.016)
h1_reexp	14.26957* (0.064)	18.74506*** (0.000)	-9.420644* (0.098)	5.143267** (0.019)
constant	2.60034* (0.095)	1.615678*** (0.000)	3.638681*** (0.004)	1.21666*** (0.000)
R^2	0.7735	-	0.7484	-
JB	49.85983*** (0.000000)	-	30.72257*** (0.000000)	-
LM_ρ	600.2572*** (0.000000)	-	193.28842*** (0.000000)	-
Wooldridge	78.093*** (0.000000)	-	78.093*** (0.000000)	-
AB(1)	24.55*** (0.000000)	-	14.56*** (0.000000)	-
AB(2)	21.89*** (0.000000)	-	7.93*** (0.000000)	-

Notes: Driscoll and Kraay (1998) standard errors are employed for calculation of t-test statistic to correct for possible cross-sectional dependence, heteroscedasticity and autocorrelation. P-values are provided in parentheses. JB is the Jarque-Berra statistics to test the normality of standardized residuals and JB $\sim\chi_2^2$ under null hypothesis. LM_ρ is the LM statistics to test for first order autocorrelation in the residuals; $LM_\rho \sim\chi_1^2$ under the assumption of no autocorrelation. Wooldridge test is the first order autocorrelation test in the residuals and it is distributed as F (1, 64) under null hypothesis. AB(1) and AB(2) tests are the first and second order autocorrelation tests developed by Arellano and Bond (1991) and asymptotically normally distributed under null hypothesis. LR_H and LM_H are the heteroscedasticity tests and have asymptotic χ^2 null distribution with 64 d.f. Pesaran's, Free's and Friedman's CD tests are cross-sectional dependence tests. First one has asymptotic N(0, 1) distribution for large T and N⟶ ∞, whereas, Friedman's test is asymptotically χ^2 distributed with 11 d.f. for fixed T and large N under the null hypothesis of cross-section independence. Critical values from Frees' Q distribution are for 10%, 5% and 1% significance levels are 0.2136, 0.2838 and 0.4252. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%.

Table 7.3. (Continued)

	Pooled OLS	Pooled FGLS	Within	FGLSDV
LR_H	538.52*** (0.000000)	-	307.17*** (0.000000)	-
LM_H	646.7027*** (0.000000)	-	261.7809*** (0.000000)	-
Pesaran's CD	-	-	22.732*** (0.000)	-
Free's CD	-	-	8.634***	-
Friedman's CD	-	-	121.343*** (0.000)	-

To estimate the model under the assumption of heterogeneous intercepts and heteroscedastic errors across provinces and province specific first order autocorrelated errors, we apply FGLSDV estimation. Results are presented in Table 7.3. Although all the coefficients are significant, signs of coefficients on lnrep and h1_reexp variables are opposed to a priori expectations.

According to comparison of estimation results obtained from pooled and fixed effects models, electricity consumption is own-price inelastic in all the estimations and only in pooled OLS estimation, electricity consumption is income elastic; in all others, income elasticity of electricity consumption is less than one.

As we have still heteroscedasticity and autocorrelation problems after accounting for some possible heterogeneity in the data which can be the resulted from omitted variables or omitted dynamics in the model and also due to data limitations, we prefer to continue with panel dynamic model estimation in Section 7.3.1.

7.2.2. Estimation Results for the Pooled and Fixed Effects Model with h2_reexc

Estimation results are given in Table 7.4. From the test for individual effects, we obtain F statistic and its p-value as 4136.2464 and 0.000, respectively. Therefore, we need to consider the heterogeneity among provinces and estimate the model by within estimation assuming that the effects are fixed. We present both fixed effects and pooled model estimation results and as there is evidence of autocorrelation and heteroscedasticity in both models, we employ pooled FGLS and FGLSDV estimation methods. In all the estimations, coefficient of lnrep and in within and FGLSDV estimations, coefficient of hdd have incorrect signs. Negative effect of h2_reexc variable is highly significant in within and FGLSDV estimations. If we compare the income elasticities from the estimations, only pooled OLS estimation results show that electricity consumption is income elastic, however from other estimations, we obtain income elasticity smaller than one implying that electricity consumption is income inelastic. In section 7.3.2, we try to solve model misspecification problem by employing dynamic panel data model.

Table 7.4 Pooled and Fixed Effects Estimations of Electricity Consumption Model with h2_reexc

Dependent variable: lnpcec	**Pooled OLS**	**Pooled FGLS**	**Fixed Effects (within estimation)**	**FGLSDV estimation**
lnpcgdp	1.229579*** (0.000)	0.860908*** (0.000)	0.361684*** (0.000)	0.345396*** (0.000)
lnrep	0.3854319* (0.076)	0.139505*** (0.000)	0.179796 (0.225)	0.081696*** (0.001)
uratio	0.36114*** (0.000)	1.314919*** (0.000)	4.092767*** (0.000)	5.243975*** (0.000)
hdd	-0.0000386 (0.120)	-3.1E-05* (0.055)	-4.8E-05 (0.117)	3.51E-06 (0.781)
cdd	0.000055 (0.601)	4.24E-05 (0.459)	0.000342 (0.134)	0.000153*** (0.002)
h2_reexc	8.040033 (0.915)	8.331892 (0.848)	-298.739*** (0.003)	-179.665*** (0.000)
constant	3.143058** (0.022)	2.867192*** (0.000)	4.033475*** (0.000)	2.105422*** (0.000)
R^2	0.7729	-	0.7584	-

Table 7.4 (Continued)

	Pooled OLS	Pooled FGLS	Within	FGLSDV
JB	47.9660*** (0.000)	-	40.41390*** (0.000)	-
LM_ρ	593.90717*** (0.000)	-	189.95981*** (0.000)	-
Wooldridge	78.650*** (0.000)	-	78.650*** (0.000)	-
AB(1)	24.35*** (0.000)	-	14.17*** (0.000)	-
AB(2)	21.92*** (0.000)	-	7.33*** (0.000)	-
LR_H	529.95*** (0.000)	-	299.92*** (0.000)	-
LM_H	643.6538*** (0.000)	-	264.1315*** (0.000)	-
Pesaran's CD	-	-	22.570*** (0.000)	-
Free's CD	-	-	8.749***	-
Friedman's CD	-	-	123.414*** (0.000)	-

Notes: Driscoll and Kraay (1998) standard errors are employed for calculation of t-test statistic to correct for possible cross-sectional dependence, heteroscedasticity and autocorrelation. P-values are provided in parentheses. JB is the Jarque-Berra statistics to test the normality of standardized residuals and JB $\sim\chi_2^2$ under null hypothesis. LM_ρ is the LM statistics to test for first order autocorrelation in the residuals; $LM_\rho \sim \chi_1^2$ under the assumption of no autocorrelation. Wooldridge test is the first order autocorrelation test in the residuals and it is distributed as F (1, 64) under null hypothesis. AB(1) and AB(2) tests are the first and second order autocorrelation tests developed by Arellano and Bond (1991) and asymptotically normally distributed under null hypothesis. LR_H and LM_H are the heteroscedasticity tests and have asymptotic χ^2 null distribution with 64 d.f. Pesaran's, Free's and Friedman's CD tests are cross-sectional dependence tests. First one has asymptotic N(0, 1) distribution for large T and N⟶ ∞, whereas, Friedman's test is asymptotically χ^2 distributed with 11 d.f. for fixed T and large N under the null hypothesis of cross-section independence. Critical values from Frees' Q distribution are for 10%, 5% and 1% significance levels are 0.2136, 0.2838 and 0.4252. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%. In FGLS estimation for pooled model, common AR(1) coefficients for all provinces is estimated as 0.7637.

7.2.3. Estimation Results for the Pooled and Fixed Effects Model with h3_ipi

The fixed effects test gives us F statistic and associated p-value as 4086.6306 and 0.000, respectively. There exist fixed effects in the model. Table 7.5 shows the estimation results for pooled and fixed effects model. If we apply OLS and within estimation methods to estimate these models, we face problems of autocorrelation and heteroscedasticity. In order to deal with autocorrelation and heteroscedasticity, we estimate the models by pooled FGLS and FGLSDV estimation methods. We observe that some of the coefficients' signs are contrary to our expectations such that signs of coefficients on lnrep and h3_ipi are positive in all the estimations and except FGLSDV, hdd has a negative effect on electricity consumption. lnpcgdp, uratio and h3_ipi have positive and significant impacts on electricity consumption. Other than pooled OLS, we obtain income elasticity less than one implying income inelastic electricity consumption. Dynamic panel data model estimations are shown in Section 7.3.3.

Table 7.5 Pooled and Fixed Effects Estimations of Electricity Consumption Model with h3_ipi

Dependent variable: lnpcec	**Pooled OLS**	**Pooled FGLS**	**Fixed Effects (within)**	**FGLSDV estimation**
lnpcgdp	1.228854*** (0.000)	0.871426*** (0.000)	0.509965*** (0.000)	0.480272*** (0.000)
lnrep	0.161148 (0.600)	0.054586 (0.184)	0.078189 (0.634)	0.045848* (0.094)
uratio	0.345462*** (0.000)	1.183544*** (0.000)	3.704108*** (0.000)	4.770785*** (0.000)
hdd	-3.9E-05* (0.078)	-4.4E-05*** (0.003)	-1.9E-05 (0.559)	9.30E-06 (0.469)
cdd	5.41E-05 (0.601)	8.39E-05 (0.141)	0.000414** (0.046)	0.000219*** (0.000)
h3_ipi	168.3852** (0.040)	88.75373*** (0.000)	138.1713*** (0.001)	63.1378*** (0.000)
constant	1.696497 (0.380)	2.329589*** (0.000)	2.607** (0.018)	1.377287*** (0.000)
R^2	0.7755	-	0.7581	-
JB	49.37538*** (0.000)	-	64.83882*** (0.000)	-
LM_ρ	595.40802*** (0.000)	-	188.85477*** (0.000)	-

Table 7.5 (Continued)

	Pooled OLS	Pooled FGLS	Within	FGLSDV
Wooldridge	78.129*** (0.000)	-	78.129*** (0.000)	-
AB(1)	24.41*** (0.000)	-	14.14*** (0.000)	-
AB(2)	21.91*** (0.000)	-	7.37*** (0.000)	-
LR_H	551.76*** (0.000)	-	307.75*** (0.000)	-
LM_H	654.6722*** (0.000)	-	280.9829*** (0.000)	-
Pesaran's CD	-	-	21.015*** (0.000)	-
Free's CD	-	-	7.950***	-
Friedman's CD	-	-	110.404*** (0.0003)	-

Notes: Driscoll and Kraay (1998) standard errors are employed for calculation of t-test statistic to correct for possible cross-sectional dependence, heteroscedasticity and autocorrelation. P-values are provided in parentheses. JB is the Jarque-Berra statistics to test the normality of standardized residuals and JB $\sim\chi_2^2$ under null hypothesis. LM_ρ is the LM statistics to test for first order autocorrelation in the residuals; $LM_\rho \sim \chi_1^2$ under the assumption of no autocorrelation. Wooldridge test is the first order autocorrelation test in the residuals and it is distributed as F (1, 64) under null hypothesis. AB(1) and AB(2) tests are the first and second order autocorrelation tests developed by Arellano and Bond (1991) and asymptotically normally distributed under null hypothesis. LR_H and LM_H are the heteroscedasticity tests and have asymptotic χ^2 null distribution with 64 d.f. Pesaran's, Free's and Friedman's CD tests are cross-sectional dependence tests. First one has asymptotic N(0, 1) distribution for large T and N$\longrightarrow \infty$, whereas, Friedman's test is asymptotically χ^2 distributed with 11 d.f. for fixed T and large N under the null hypothesis of cross-section independence. Critical values from Frees' Q distribution are for 10%, 5% and 1% significance levels are 0.2136, 0.2838 and 0.4252. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%. In FGLS estimation for pooled model, common AR(1) coefficients for all provinces is estimated as 0.7622.

7.2.4. Estimation Results for the Pooled and Fixed Effects Model with h4_poil

We present the estimation results in Table 7.6. We perform test for the presence of individual effects and results of test [F statistic (p-value)= 3917.549 (0.000)] show that there exists fixed effects in our model. Diagnostic tests results reveal the evidence for autocorrelation and heteroscedasticity in the residuals obtained from the pooled and fixed effects models. We apply FGLS and FGLSDV estimation methods to account for these problems. From FGLSDV estimation, we can say that all the variables except h4_poil positively and significantly affect electricity consumption; however positive sign on the coefficient of lnrep is contrary to the theoretical expectations. In addition, result of FGLSDV estimation show that electricity consumption is income inelastic opposite to result of OLS estimation. As in the other models with different volatility variables, in section 7.3.4, to deal with misspecification problem, we estimate dynamic panel data model using various methods.

Table 7.6 Pooled and Fixed Effects Estimations of Electricity Consumption Model with h4_poil

Dependent Var.: lnpcec	**Pooled OLS**	**Pooled FGLS**	**Fixed Effects (within estimation)**	**FGLSDV estimation**
lnpcgdp	1.229135*** (0.000)	0.855349*** (0.000)	0.516946*** (0.000)	0.452744*** (0.000)
lnrep	0.35979 (0.140)	0.141169*** (0.000)	0.176936 (0.190)	0.089913*** (0.000)
uratio	0.360037*** (0.000)	1.317998*** (0.000)	4.29082*** (0.000)	5.196806*** (0.000)
hdd	-3.8E-05 (0.103)	-3.3E-05** (0.046)	-2.2E-05 (0.419)	2.29E-05* (0.090)
cdd	5.37E-05 (0.608)	3.91E-05 (0.495)	0.000409 (0.123)	0.000176*** (0.001)
h4_poil	3.337359 (0.690)	-0.6217 (0.795)	0.267354 (0.955)	0.314506 (0.802)
constant	2.974876** (0.052)	2.917302*** (0.000)	2.983155*** (0.001)	1.536753*** (0.000)
R^2	0.773	-	0.7468	-
JB	47.05463*** (0.000)	-	35.72885*** (0.000)	-
LM_ρ	594.11285*** (0.000)	-	207.07913*** (0.000)	-
Wooldridge	76.915*** (0.000)	-	76.915*** (0.000)	-

Table 7.6. (Continued)

	Pooled OLS	Pooled FGLS	Within	FGLSDV
AB(1)	24.36*** (0.000)	-	14.75*** (0.000)	-
AB(2)	21.83*** (0.000)	-	8.35*** (0.000)	-
LR_H	530.19*** (0.000)	-	310.51*** (0.000)	-
LM_H	642.578 (0.000)	-	273.9791 (0.000)	-
Pesaran's CD	-	-	20.615*** (0.000)	-
Free's CD	-	-	9.089***	-
Friedman's CD	-	-	107.708*** (0.0005)	-

Notes: Driscoll and Kraay (1998) standard errors are employed for calculation of t-test statistic to correct for possible cross-sectional dependence, heteroscedasticity and autocorrelation. P-values are provided in parentheses. JB is the Jarque-Berra statistics to test the normality of standardized residuals and JB $\sim\chi^2_2$ under null hypothesis. LM_ρ is the LM statistics to test for first order autocorrelation in the residuals; $LM_\rho \sim \chi^2_1$ under the assumption of no autocorrelation. Wooldridge test is the first order autocorrelation test in the residuals and it is distributed as F (1, 64) under null hypothesis. AB(1) and AB(2) tests are the first and second order autocorrelation tests developed by Arellano and Bond (1991) and asymptotically normally distributed under null hypothesis. LR_H and LM_H are the heteroscedasticity tests and have asymptotic χ^2 null distribution with 64 d.f. Pesaran's, Free's and Friedman's CD tests are cross-sectional dependence tests. First one has asymptotic N(0, 1) distribution for large T and N$\longrightarrow \infty$, whereas, Friedman's test is asymptotically χ^2 distributed with 11 d.f. for fixed T and large N under the null hypothesis of cross-section independence. Critical values from Frees' Q distribution are for 10%, 5% and 1% significance levels are 0.2136, 0.2838 and 0.4252. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%. In FGLS estimation for pooled model, common AR(1) coefficients for all provinces is estimated as 0.7636.

7.2.5. Estimation Results for the Pooled and Fixed Effects Model with h5_nexcr

In Table 7.7, we present the estimation and diagnostic test results of pooled and fixed effects models estimated by OLS, FGLS, within and FGLSDV estimation methods. As tests for individual effects [F statistic (p-value)=3944.0012 (0.000)], autocorrelation and heteroscedasticity show that there exists heterogeneity, autocorrelation and heteroscedasticity, we consider the estimation results of fixed effects model by FGLSDV estimation method. All the coefficients are statistically significant, however, the sign of coefficient on lnrep is not in line with the theoretical expectations. From estimation results, we can infer that electricity consumption is income inelastic. In section 7.3.5, we continue with the dynamic model estimation by including the lagged dependent variable into the model in order to deal with misspecification problem.

Table 7.7 Pooled and Fixed Effects Estimations of Electricity Consumption Model with h5_nexcr

Dependent variable: lnpcec	**Pooled OLS**	**Pooled FGLS**	**Fixed Effects (within estimation)**	**FGLSDV estimation**
lnpcgdp	1.248676*** (0.000)	0.961901*** (0.000)	0.48718*** (0.000)	0.488895*** (0.000)
lnrep	0.227759 (0.441)	-0.02537 (0.548)	0.224176 (0.233)	0.057925* (0.057)
uratio	0.350245*** (0.000)	1.274492*** (0.000)	4.306862*** (0.000)	5.118782*** (0.000)
hdd	-3E-05 (0.199)	7.09E-06 (0.638)	-3.4E-05 (0.316)	2.86E-05** (0.032)
cdd	6.67E-05 (0.534)	-2.97E-06 (0.955)	0.000432 (0.112)	0.00015*** (0.005)
h5_nexcr	115.6109* (0.081)	109.3943*** (0.000)	-31.8504 (0.417)	25.23086** (0.045)
constant	2.111627 (0.258)	1.375589*** (0.000)	3.413373** (0.019)	1.244059*** (0.000)
R^2	0.7743	-	0.7474	-
JB	50.16123*** (0.000)	-	31.52480*** (0.000)	-
LM_ρ	600.31256*** (0.000)	-	200.7972*** (0.000)	-
Wooldridge	76.725*** (0.000)	-	76.725*** (0.000)	-
AB(1)	24.45*** (0.000)	-	14.61*** (0.000)	-
AB(2)	22.00*** (0.000)	-	8.04*** (0.000)	-
LR_H	544.23*** (0.000)	-	310.14*** (0.000)	-
LM_H	648.9735*** (0.000)	-	266.6808*** (0.000)	-

Table 7.7 (Continued)

	Pooled OLS	**Pooled FGLS**	**Within**	**FGLSDV**
Pesaran's CD	-	-	21.465*** (0.000)	-
Free's CD	-	-	8.596***	-
Friedman's CD	-	-	110.643*** (0.0003)	-

Notes: Driscoll and Kraay (1998) standard errors are employed for calculation of t-test statistic to correct for possible cross-sectional dependence, heteroscedasticity and autocorrelation. P-values are provided in parentheses. JB is the Jarque-Berra statistics to test the normality of standardized residuals and JB $\sim\chi_2^2$ under null hypothesis. LM_ρ is the LM statistics to test for first order autocorrelation in the residuals; $LM_\rho\sim\chi_1^2$ under the assumption of no autocorrelation. Wooldridge test is the first order autocorrelation test in the residuals and it is distributed as F (1, 64) under null hypothesis. AB(1) and AB(2) tests are the first and second order autocorrelation tests developed by Arellano and Bond (1991) and asymptotically normally distributed under null hypothesis. LR_H and LM_H are the heteroscedasticity tests and have asymptotic χ^2 null distribution with 64 d.f. Pesaran's, Free's and Friedman's CD tests are cross-sectional dependence tests. First one has asymptotic N(0, 1) distribution for large T and N$\longrightarrow\infty$, whereas, Friedman's test is asymptotically χ^2 distributed with 11 d.f. for fixed T and large N under the null hypothesis of cross-section independence. Critical values from Frees' Q distribution are for 10%, 5% and 1% significance levels are 0.2136, 0.2838 and 0.4252. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%. In FGLS estimation for pooled model, common AR(1) coefficients for all provinces is estimated as 0.7743.

7.2.6. Estimation Results for the Pooled and Fixed Effects Model with h6_ise100

Table 7.8 shows the estimation results of pooled and fixed effects model with h6_ise100. From Table 7.8, we can see that there are significant differences in results based on the estimation method employed, however, we observe significant and positive effect of lnpcgdp and uratio in all the estimation results. Diagnostic tests and fixed effects test [F statistic(p-value) = 3943.6802(0.000)] indicate presence of autocorrelation, heteroscedasticity and individual effects. In order to account all these problems simultaneously, we estimate fixed effects model by FGLSDV estimation method. All the coefficients are significant except the one on h6_ise100 variable and the signs of coefficients on lnrep and h6_ise100 were expected to be negative but we obtain positive coefficients. Comparison of income elasticities among the estimations reveals that electricity consumption is income inelastic excluding pooled OLS estimation. Section 7.3.6, we perform dynamic panel data model estimation for model misspecification problem.

Table 7.8 Pooled and Fixed Effects Estimations of Electricity Consumption Model with h6_ise100

Dependent variable: lnpcec	**Pooled OLS**	**Pooled FGLS**	**Fixed Effects (within estimation)**	**FGLSDV estimation**
lnpcgdp	1.234296*** (0.000)	0.888388*** (0.000)	0.512347*** (0.000)	0.456771*** (0.000)
lnrep	0.266253 (0.434)	0.057121 (0.163)	0.190958 (0.267)	0.083888*** (0.002)
uratio	0.35733*** (0.000)	1.239138*** (0.000)	4.321028*** (0.000)	5.158115*** (0.000)
hdd	-3.7E-05 (0.121)	-0.00002 (0.183)	-2.3E-05 (0.459)	2.11E-05* (0.097)
cdd	5.29E-05 (0.607)	1.61E-05 (0.772)	0.000427 (0.131)	0.000168*** (0.002)
h6_ise100	3.009195 (0.378)	3.376033*** (0.000)	-0.46139 (0.783)	0.318835 (0.470)
constant	2.39018 (0.260)	2.226275*** (0.000)	3.077273*** (0.009)	1.515487*** (0.000)
R^2	0.7736	-	0.7469	-
JB	46.56593*** (0.000)	-	34.95786*** (0.000)	-
LM_ρ	599.52679*** (0.000)	-	204.62399*** (0.000)	-
Wooldridge	76.199*** (0.000)	-	76.199*** (0.000)	-
AB(1)	24.45*** (0.000)	-	14.66 *** (0.000)	-
AB(2)	21.96*** (0.000)	-	8.12*** (0.000)	-
LR_H	533.61*** (0.000)	-	309.50*** (0.000)	-
LM_H	642.1845*** (0.000)	-	274.7063*** (0.000)	-

Table 7.8 (Continued)

	Pooled OLS	**Pooled FGLS**	**Within**	**FGLSDV**
Pesaran's CD	-	-	20.167*** (0.000)	-
Free's CD	-	-	8.767***	-
Friedman's CD	-	-	105.298*** (0.0009)	-

Notes: Driscoll and Kraay (1998) standard errors are employed for calculation of t-test statistic to correct for possible cross-sectional dependence, heteroscedasticity and autocorrelation. P-values are provided in parentheses. JB is the Jarque-Berra statistics to test the normality of standardized residuals and JB $\sim\chi_2^2$ under null hypothesis. LM_ρ is the LM statistics to test for first order autocorrelation in the residuals; $LM_\rho \sim \chi_1^2$ under the assumption of no autocorrelation. Wooldridge test is the first order autocorrelation test in the residuals and it is distributed as F (1, 64) under null hypothesis. AB(1) and AB(2) tests are the first and second order autocorrelation tests developed by Arellano and Bond (1991) and asymptotically normally distributed under null hypothesis. LR_H and LM_H are the heteroscedasticity tests and have asymptotic χ^2 null distribution with 64 d.f. Pesaran's, Free's and Friedman's CD tests are cross-sectional dependence tests. First one has asymptotic N(0, 1) distribution for large T and N$\longrightarrow\infty$, whereas, Friedman's test is asymptotically χ^2 distributed with 11 d.f. for fixed T and large N under the null hypothesis of cross-section independence. Critical values from Frees' Q distribution are for 10%, 5% and 1% significance levels are 0.2136, 0.2838 and 0.4252. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%. In FGLS estimation for pooled model, common AR(1) coefficients for all provinces is estimated as 0.7713.

7.3. Dynamic Panel Data Model Estimation Results

In order to deal with autocorrelation, we estimate the following dynamic panel data model;

$$lnpcec = \alpha_1 lnpcec_{-1} + X\alpha_2 + D_\mu \mu + \varepsilon, \tag{7.2}$$

where X = (lnpcgdp lnrep uratio hdd cdd h) and h is one of the volatility variables as, h1_reexp, h2_reexc, h3_ipi, h4_poil, h5_nexcr and h6_ise100.

We formulate this dynamic partial adjustment model by following steps:

1. We have a static electricity consumption model (desired level of electricity consumption) as in below equation:

$$lnpcec^* = \beta * lnpcgdp + \gamma * lnrep + \theta * uratio + \vartheta * hdd + \varphi * cdd + \lambda * h + \mathrm{D}_{\mu}\mu_{*} + u \quad (7.3)$$

2. **2.** We formalize partial adjustment mechanism in equation (7.4) to consider adjustment lags of current electricity consumption to the long-run equilibrium electricity consumption after a shock. Here, π shows the adjustment speed.

$$lnpcec - lnpcec_{-1} = \pi(lnpcec^* - lnpcec_{-1}) \quad (7.4)$$

3. **3.** To obtain equation (7.2), we replace $lnpcec^*$ in equation (7.4) with $lnpcec^*$ in equation (7.3) and solve for $lnpcec$.

In the next sections, we estimate dynamic panel data model by employing different volatility variables.

7.3.1. Estimation Results for the Dynamic Panel Data Model with h1_reexp

Estimation results of the dynamic panel data model are given in Table 7.9. Ignoring fixed effects, we perform OLS estimation in which dynamic panel bias problem emerges as shown by Nickell (1981).

We can consider fixed effects in our model and proceed with within estimation of the dynamic panel data model. Within transformation of the model is as follows;

$$N_{\mu}\mathrm{lnpcec} = \alpha_1(N_{\mu}\mathrm{lnpcec}_{-1}) + N_{\mu}\mathrm{X}\alpha_2 + N_{\mu}\varepsilon, \quad (7.5)$$
$$\text{where } \mathrm{X} = (\mathrm{lnpcgdp} \quad \mathrm{lnrep} \quad \mathrm{uratio} \quad \mathrm{hdd} \quad \mathrm{cdd} \quad \mathrm{h})$$

In this case also, there exists asymptotic correlation between $N_{\mu} \ln pcec_{-1}$ and $N_{\mu}\varepsilon$ and thus, problem of dynamic panel bias discussed by Nickell (1981). OLS and within estimations of the dynamic model show us that bounds for the good estimate of the coefficient on the lagged dependent variable lie between 0.945481 and 0.677389.

To overcome asymptotic correlation problem in within estimation, $N_{\mu}X_{-1}$ is used as instrument for $N_{\mu}\ln pcec_{-1}$ suggested by Balestra and Nerlove (1966) and Sevestre and Trognon (1996). Under the assumption that the other regressors are exogenous (BN1), estimation results show that the coefficient estimate of the lagged dependent variable is in the range of the good estimates for the true parameter. Hansen test reject the validity of overidentifying restrictions. Therefore, we assume apart from $N_{\mu}\ln pcec_{-1}$, $N_{\mu}\ln pcgdp$ is endogenous in the estimation and $N_{\mu}\ln pcgdp_{-1}$ is used as instrument for $N_{\mu}\ln pcgdp$ (BN2). According to Hansen test, overidentifying restrictions are not valid and therefore there is still misspecification in the model.

To get rid of fixed effects, we use first difference transformation of the model following Anderson and Hsiao (1981, 1982) approach;

$$\Delta \text{lnpcec} = \alpha_1 \Delta \text{lnpcec}_{-1} + \Delta X \alpha_2 + \Delta\varepsilon, \tag{7.6}$$
$$\text{where } X = (\text{lnpcgdp} \quad \text{lnrep} \quad \text{uratio} \quad \text{hdd} \quad \text{cdd} \quad \text{h})$$

Here, $E(\Delta\ln pcec_{-1}\Delta\varepsilon) \neq 0$, therefore, we instrument $\Delta\ln pcec_{-1}$ by $\ln pcec_{-2}$. We estimate for the two cases depending on the exogeneity assumption for lnpcgdp. In the first case (AH1), we assume all the other regressors are exogenous, whereas, in the second estimation (AH2), we treat Δlnpcgdp as endogeneous and instrument it by lnpcgdp_{-2}. Based on AB Autocorrelation test for both AH1 and AH2 estimations, we can say that there is no second order autocorrelation.

To increase efficiency, we continue estimations of dynamic panel data model following Arellano-Bond Approach (AB) in which first difference transformation and GMM estimation method is used. We take the following variables as exogenous:

real electricity prices (lnrep) as they are under the regulation of government, urbanization ratio (uratio), temperature variables (hdd and cdd); and volatility variable (h1_reexp). Estimation is performed by two-step difference GMM to ensure consistency and asymptotic efficiency of estimators. Downward bias in the two-step standard errors are corrected by Windmeijer (2005) finite-sample correction. Number of moments is determined by downward testing procedure proposed by Andrews and Lu (2001). As in the AH2 estimation, second lag of lnpcec is used as instrument for differenced lagged lnpcec and Δlnpcgdp is instrumented by lnpcgdp_{-2}, but here, we use one instrument for each time period, variable and lag distance.

Table 7.9 shows the estimation results. The negative sign of coefficient on cdd and positive sign of coefficient on h1_reexp are contrary to what we expect. Signs of the all other coefficients are proper to our a priori expectations. Effects of temperature and volatility variables are statistically insignificant. Model is correctly specified according to diagnostic tests as, Arellano-Bond and Hansen tests indicate the absence of second and third order autocorrelation and that overidentifying restrictions are valid, respectively.

As the coefficient on lnpcec_{-1} is outside the interval for good parameter estimate, we apply Blundell and Bond (1998) "system" GMM estimation which is found to be more stable and efficient compared to AB "difference" GMM estimation. In system GMM estimation, we estimate a system of equations composed of level equation and differenced equation and therefore additional moment conditions are formed. For the level variables in level equation, lags of own first differences are employed as instruments. Here, we need additional assumption that these differences are not correlated with fixed effects. For each variable, time period and lag distance, one instrument is used.

System GMM estimation results of panel dynamic model given in Table 7.9 under BB1 estimation, reveal that coefficients on all the variables except uratio have the expected signs but only coefficients of lnpcgdp and lnrep are significant at most 5%

significance level. Specification of the model is supported by Hansen and Arrellano-Bond tests.

Table 7.9 Alternative Estimates of Dynamic Panel Data Model with h1_reexp, Number of Groups=65

lnpcec\Methods	**OLS**	**WITHIN**	**AB**	**BB1**	**BB2**
lnpcec $_{-1}$	0.9455*** (0.000)	0.6774*** (0.000)	0.6979*** (0.000)	0.8755*** (0.000)	0.7017*** (0.000)
lnpcgdp	0.0750*** (0.000)	0.2257*** (0.000)	0.3606*** (0.000)	0.1799** (0.010)	0.3615*** (0.000)
lnrep	-0.0747** (0.047)	-0.0653 (0.147)	-0.1439*** (0.002)	-0.0928** (0.027)	-0.1448*** (0.002)
uratio	-0.0241 (0.523)	1.4937*** (0.000)	1.2420* (0.086)	-0.0099 (0.902)	1.21128* (0.090)
hdd	1.23E-05* (0.088)	6.40E-06 (0.747)	2.69E-05 (0.189)	1.73E-05 (0.229)	0.00003 (0.184)
cdd	2.67E-05 (0.223)	6.77E-05 (0.402)	-0.0001 (0.306)	4.01E-05 (0.289)	-0.0001 (0.295)
h1_reexp	-7.1092*** (0.009)	-3.6084 (0.244)	4.1602 (0.318)	-3.7063 (0.250)	4.2413 (0.309)
constant	-0.36322 (0.127)	-0.0299 (0.939)	-	-0.5089 (0.136)	-1.1258** (0.022)
Hansen J Test Statistic	-	-	50.32 (0.177)	55.71 (0.180)	50.24 (0.179)
AB Test – 1	-1.51 (0.1314)	-0.2 (0.8400)	-3.74*** (0.0000)	-4.15*** (0.0000)	-3.74*** (0.0000)
AB Test - 2	-0.46 (0.6447)	-0.77 (0.4430)	0.05 (0.9630)	-0.2 (0.8390)	0.05 (0.9640)
AB Test - 3	1.62 (0.1050)	0.11 (0.9128)	1.64 (0.1000)	1.98** (0.0480)	1.64 (0.1010)
Instruments #	-	-	49	55	50
Pesaran CD test	5.85*** (0.000)	5.74*** (0.000)	0.93 (0.355)	5.53*** (0.000)	2.81*** (0.005)

Notes: P-values are in parentheses. Hansen J statistic for testing the validity of instruments is asymptotically χ^2 distributed with d.f.=overidentification degree. Overidentification degrees are 42, 47 and 42 in AB, BB1 and BB2, respectively. AB(1), AB(2) and AB(3) tests are the first, second and third order autocorrelation tests developed by Arellano and Bond (1991) and asymptotically N(0,1) under H_0. *, **, *** shows the statistical significance of test statistic and coefficient at 10%, 5%, 1%.

In BB2 estimation, we account for the possibility of correlation between fixed effects and $lnpcec_{-1}$, lnpcgdp, lnrep, uratio, hdd and cdd variables by excluding them from the levels equation. As, only h1_reexp variable is left in the levels equation, the result does not change so much when we compare with AB estimation results. From the results, we infer that electricity consumption is a normal good ; it is inelastic with respect to both income and price. 1% increase in income is associated with 0.36% increase in electricity consumption and 1% increase in electricity price causes an 0.14% decrease in electricity consumption. However, as there is cross sectional dependence problem, we estimate the model by employing the cross sectionally demeaned series. Estimation results are given in Table 7.10. We obtain similar results and Pesaran (2004) cross sectional dependence test indicates that cross sectional dependency declines.

Table 7.10 System GMM Estimation Results of Dynamic Panel Data Model with h1_reexp and cross sectional demeaned series, Number of Groups=65

lnpcec*\Methods	**BB2**	
$lnpcec^*_{-1}$	0.5745179	(0.000)***
lnpcgdp*	0.4274584	(0.003)***
lnrep*	-0.5914244	(0.070)*
uratio*	1.380784	(0.041)**
hdd*	0.000012	(0.726)
cdd*	-2.72E-06	(0.981)
h1_reexp	-0.7090909	(0.808)
constant	-0.0000855	(0.998)
Hansen J Test Statistic	45.13	(0.142)
AB Test – 1	-3.20	(0.001)***
AB Test - 2	-0.15	(0.884)
AB Test - 3	1.73	(0.084)*
Instruments #	44	
Pesaran CD test	-2.08	(0.038)**

Notes: P-values are in parentheses. Hansen J statistic for testing the validity of instruments is asymptotically χ^2 distributed with d.f.=overidentification degree. Overidentification degree is 36. AB(1), AB(2) and AB(3) tests are the first, second and third order autocorrelation tests developed by Arellano and Bond (1991) and asymptotically N(0,1) under H_0. *, **, *** shows the statistical significance of test statistic and coefficient at 10%, 5%, 1%.

7.3.2. Estimation Results for the Dynamic Panel Data Model with h2_reexc

We follow the same steps as in the estimation of model with h1_reexp. Results of estimations are given in Table 7.11. There is endogeneity problem in OLS and within estimation of the dynamic panel data model. The estimates of coefficient on $lnpcec_{-1}$ in OLS and within estimation are (0.943982, 0.669626) giving the interval for good estimates of true parameter. To overcome endogeneity problem, we apply the estimation methods proposed by Balestra and Nerlove (1966), Anderson and Hsiao (1981 and 1982), Arellano-Bond (1991) and Blundell and Bond (1998). BN1 estimation results show that there is misspecification in the model indicated by Hansen test. When we put the assumption that lnpcgdp is endogenous and instrument it with its own first lag in BN2 estimation, we obtain satisfactory results from specification tests as overidentifying restrictions are validated by Hansen test and Arrellano-Bond tests imply that there is no evidence of autocorrelation. However, estimates of coefficients on lnpcgdp and cdd have incorrect signs.

Up to here, we get rid of fixed effects by within transformation of the data. First difference transformation of the model is employed in AH1, AH2, AB, BB1 and BB2 estimations. Although in AH1 estimation, we treat all the variables as exogenous, AH2 estimation is performed assuming lnpcgdp is endogenous and its difference form is instrumented with its own second lag. There are slight differences between these two estimations. Signs of coefficients except cdd in both and h2_reexc in AH2 are in line with a priori expectations. We obtain insignificant estimate of coefficient on lnpcgdp, in AH2 estimation. In AH1 and AH2 estimations, as the number of parameters to be estimated are equal to the number of instruments, we have just-identified situation. Due to the same reason as before, that is for efficiency improvement over AH estimations, we continue with Arellano-Bond and Blundell-Bond approaches that allow us to increase the number of moment conditions leading over-identified case. Diagnostic tests in AB, BB1 and BB2 estimations support the model specification. AB estimation results are almost same with that obtained from BB2 estimation.

Table 7.11 Alternative Estimates of Dynamic Panel Data Model with h2_reexc, Number of Groups=65

lnpcec\ Methods	**OLS**	**WITHIN**	**AB**	**BB1**	**BB2**
lnpcec $_{-1}$	0.944*** (0.00)	0.670*** (0.00)	0.624*** (0.00)	0.829*** (0.00)	0.533288*** (0.0000)
lnpcgdp	0.076*** (0.00)	0.194*** (0.00)	0.297*** (0.002)	0.201*** (0.01)	0.239229*** (0.0070)
lnrep	-0.133*** (0.00)	-0.072* (0.07)	-0.109* (0.06)	-0.099** (0.02)	-0.1191*** (0.0090)
uratio	-0.022 (0.56)	1.497*** (0.00)	1.880** (0.02)	0.094 (0.4450)	2.905068*** (0.0000)
hdd	1.24E-05* (0.09)	6.36E-06 (0.74)	2.05E-05 (0.3330)	2.38E-06 (0.9180)	2.03E-05 (0.2680)
cdd	2.33E-05 (0.29)	3.07E-05 (0.70)	-3.7E-05 (0.7150)	9.09E-06 (0.8620)	-3.4E-05 (0.7260)
h2_reexc	-95.1*** (0.003)	-104.1*** (0.01)	-37.472 (0.5600)	-80.8244 (0.1710)	-66.8984 (0.2520)
constant	-0.658*** (0.002)	0.181 (0.6230)	-	-0.31018 (0.5490)	-0.16476 (0.8200)
Hansen J Test Statistic	-	-	53.98 (0.1020)	48.28 (0.1230)	54.96 (0.124)
AB Test – 1	-1.32 (0.1875)	0.06 (0.9509)	-3.51*** (0.00)	-4.11*** (0.0000)	-3.42*** (0.001)
AB Test - 2	-0.73 (0.4636)	-1.05 (0.2958)	0.11 (0.91)	-0.48 (0.6300)	0.19 (0.846)
AB Test - 3	1.55 (0.1210)	-0.09 (0.9322)	1.81 (0.07)	1.97** (0.0490)	2.09** (0.037)
Instruments #	-	-	49	46	52
Pesaran CD Test	6.38*** (0.000)	4.91*** (0.000)	1.87* (0.061)	6.17*** (0.000)	2.40** (0.016)

Notes: P-values are in parentheses. Hansen J statistic for testing the validity of instruments is asymptotically χ^2 distributed with d.f.=overidentification degree. Overidentification degrees are 42, 38 and 44 in AB, BB1 and BB2, respectively. AB(1), AB(2) and AB(3) tests are the first, second and third order autocorrelation tests developed by Arellano and Bond (1991) and asymptotically N(0,1) under H_0. *, **, *** shows the statistical significance of test statistic and coefficient at 10%, 5%, 1%.

Considering possible correlation between fixed effects and lnpcec$_{-1}$, lnpcgdp, lnrep, uratio, hdd and cdd variables in BB2 estimation affect the sign and magnitude of cdd coefficient, statistical significance of uratio coefficient and magnitude of lnpcec$_{-1}$

coefficient compared to BB1 estimation. In Table 7.11, results show that electricity consumption is income and price inelastic. 1% increase in income is associated with 0.23% increase in electricity consumption and 1% increase in electricity price causes an 0.11% decrease in electricity consumption. Because there is cross sectional dependence problem, we repeat the estimation by using the cross sectional demeaned series. Estimation results are given in Table 7.12. Similar results are obtained and according to Pesaran (2004) cross sectional dependence test, we observe decline in cross sectional dependency.

Table 7.12 System GMM Estimation Results of Dynamic Panel Data Model with h2_reexc and cross sectional demeaned series, Number of Groups=65

lnpcec*\Methods	**BB2**	
lnpcec*$_{-1}$	0.5745179	(0.000)***
lnpcgdp*	0.4274584	(0.003)***
lnrep*	-0.5914244	(0.068)*
uratio*	1.380784	(0.039)**
hdd*	0.000012	(0.726)
cdd*	-2.72E-06	(0.981)
h2_reexc	-16.40724	(0.638)
constant	0.0066745	(0.840)
Hansen J Test Statistic	45.13	(0.142)
AB Test – 1	-3.19	(0.001)***
AB Test - 2	-0.15	(0.882)
AB Test - 3	1.75	(0.081)*
Instruments #	44	
Pesaran CD test	-2.14	(0.032)**

Notes: P-values are in parentheses. Hansen J statistic for testing the validity of instruments is asymptotically χ^2 distributed with d.f.=overidentification degree. Overidentification degree is 36. AB(1), AB(2) and AB(3) tests are the first, second and third order autocorrelation tests developed by Arellano and Bond (1991) and asymptotically N(0,1) under H_0. *, **, *** shows the statistical significance of test statistic and coefficient at 10%, 5%, 1%.

7.3.3. Estimation Results for the Dynamic Panel Data Model with h3_ipi

We present the estimation results of dynamic panel data model for OLS, within, AB, BB1 and BB2 estimations in Table 7.13.

Table 7.13 Alternative Estimates of Dynamic Panel Data Model with h3_ipi, Number of Groups=65

lnpcec\Methods	**OLS**	**WITHIN**	**AB**	**BB1**	**BB2**
lnpcec $_{-1}$	0.939*** (0.000)	0.644*** (0.000)	0.433*** (0.000)	0.791*** (0.000)	0.548*** (0.000)
lnpcgdp	0.088*** (0.000)	0.252*** (0.000)	0.382*** (0.000)	0.279*** (0.000)	0.379*** (0.000)
lnrep	-0.198*** (0.000)	-0.177*** (0.000)	-0.184*** (0.000)	-0.185*** (0.000)	-0.174*** (0.000)
uratio	-0.028 (0.462)	1.198*** (0.000)	2.466*** (0.001)	0.030 (0.767)	1.598** (0.038)
hdd	0.000014* (0.050)	1.35E-06 (0.944)	-1.88E-06 (0.906)	1.31E-05 (0.367)	9.96E-07 (0.957)
cdd	2.89E-05 (0.186)	7.92E-05 (0.314)	2.83E-05 (0.748)	4.68E-05 (0.332)	-3.2E-05 (0.710)
h3_ipi	46.11*** (0.008)	82.76*** (0.000)	84.01*** (0.000)	67.292*** (0.004)	74.73*** (0.001)
constant	-1.143*** (0.000)	-0.49435 (0.122)	-	-1.021*** (0.002)	-0.59323 (0.160)
Hansen J Test Statistic	-	-	49.68 (0.194)	43.45 (0.251)	44.25 (0.163)
AB Test – 1	-1.13 (0.2581)	0.66 (0.5105)	-3.29*** (0.001)	-4.05*** (0.000)	-3.76*** (0.000)
AB Test - 2	-0.43 (0.6694)	-0.69 (0.4932)	-0.18 (0.859)	-0.09 (0.930)	-0.02 (0.985)
AB Test - 3	1.61 (0.1076)	-0.1 (0.9172)	1.72* (0.086)	1.91* (0.056)	1.71* (0.086)
Instruments #	-	-	49	46	44
Pesaran CD Test	6.24*** (0.000)	1.80* (0.071)	0.65 (0.517)	3.62*** (0.000)	1.28 (0.200)

Notes: P-values are in parentheses. Hansen J statistic for testing the validity of instruments is asymptotically χ^2 distributed with d.f.=overidentification degrees which are 42, 38 and 36 in AB, BB1 and BB2, respectively. AB(1), AB(2) and AB(3) tests are the first, second and third order autocorrelation tests developed by Arellano and Bond (1991) and asymptotically N(0,1) under H_0. *, **, *** shows the statistical significance of test statistic and coefficient at 10%, 5%, 1%.

Upper and lower limits for the interval of the good true parameter estimates for $lnpcec_{-1}$ variable found from OLS and within estimation are (0.938816, 0.64378). Comparisons of BN1, BN2, AH1, AH2, AB, BB1 and BB2 estimations employed for dealing with the dynamic panel bias problem show that only in BN1 estimation there is evidence of misspecification in the model indicated by Hansen test. Estimate of coefficient on $lnpcec_{-1}$ varies from 0.433127 to 0.791046. Coefficient estimates in some estimations have incorrect signs such as hdd in BN1 and AB estimations and cdd in BB2 estimation. In all the estimations, we observe positive and significant impact of h3_ipi on lnpcec except for AH2 estimation and also that temperature variables do not have significant effects. In AH2 estimation, only lnrep has statistically significant coefficient at 10% significance level. Coefficients on uratio in AH1 and BB1 estimations and lnpcgdp in BN2 estimation are statistically insignificant. Our estimation results based on BB2 estimation show that electricity consumption is inelastic with respect to income and price.

7.3.4. Estimation Results for the Dynamic Panel Data Model with h4_poil

Table 7.14 shows the estimation results of dynamic panel data model. Interval for the good parameter estimates of $lnpcec_{-1}$ variable is (0.943064, 0.681308) obtained from OLS estimate and within estimate of coefficient on $lnpcec_{-1}$ variable. In OLS and within estimations, there is problem of dynamic panel bias. We perform BN1, BN2, AH1, AH2, AB, BB1 and BB2 estimations to consider this problem. However, Hansen test indicates misspecification in BN1 estimation which only takes into account dynamic panel bias. If we take lnpcgdp as endogenous and instrument it as in BN2 estimation, we solve misspecification problem. In AH1 and AH2 estimations, because there are no overidentifying restrictions, we cannot perform Hansen test, but Arellano-Bond autocorrelation tests imply that model is correctly specified. To obtain efficiency gains, we increase the number of moment conditions in AB, BB1 and BB2 estimations. Diagnostic tests reveal that there is no autocorrelation and overidentifying restrictions are valid, thus there is no evidence of misspecification in the model.

Table 7.14 Alternative Estimates of Dynamic Panel Data Model with h4_poil, Number of Groups=65

lnpcec\Methods	**OLS**	**WITHIN**	**AB**	**BB1**	**BB2**
$lnpcec_{-1}$	0.943*** (0.000)	0.681*** (0.000)	0.714*** (0.000)	0.852*** (0.000)	0.498*** (0.000)
lnpcgdp	0.084*** (0.000)	0.249*** (0.000)	0.280*** (0.000)	0.237*** (0.000)	0.348*** (0.000)
lnrep	-0.106*** (0.006)	-0.085** (0.031)	-0.115*** (0.009)	-0.096** (0.019)	-0.116*** (0.008)
uratio	-0.025 (0.515)	1.517*** (0.000)	1.331* (0.080)	-0.002 (0.984)	3.074*** (0.000)
hdd	1.47E-05** (0.041)	8.78E-06 (0.655)	1.01E-05 (0.605)	2.53E-05 (0.115)	1.39E-05 (0.464)
cdd	3.03E-05 (0.168)	6.03E-05 (0.453)	-7.6E-05 (0.474)	5.13E-05 (0.248)	-3.4E-05 (0.723)
h4_poil	-1.169 (0.455)	-1.503 (0.397)	-1.874 (0.231)	-0.778 (0.638)	-2.27714 (0.225)
constant	-0.574** (0.017)	-0.287 (0.370)	-	-0.657* (0.060)	-0.51435 (0.305)
Hansen J Test Statistic	-	-	35.3 (0.131)	56.21 (0.168)	56.42 (0.189)
AB Test – 1	-1.09 (0.2764)	0.03 (0.9742)	-3.85*** (0.000)	-4.14*** (0.000)	-3.37*** (0.001)
AB Test - 2	-0.42 (0.6749)	-0.72 (0.4725)	0.08 (0.938)	-0.25 (0.806)	0.36 (0.717)
AB Test - 3	1.67* (0.0946)	0.13 (0.8939)	1.87* (0.062)	1.93* (0.053)	1.81* (0.070)
Instruments #	-	-	34	55	56
Pesaran CD Test	8.66*** (0.000)	4.46*** (0.000)	0.53*** (0.596)	6.33*** (0.000)	1.55 (0.121)

Notes: P-values are in parentheses. Hansen J statistic for testing the validity of instruments is asymptotically χ^2 distributed with d.f.=overidentification degree. Overidentification degrees are 27, 47 and 48 in AB, BB1 and BB2, respectively. AB(1), AB(2) and AB(3) tests are the first, second and third order autocorrelation tests developed by Arellano and Bond (1991) and asymptotically N(0,1) under H_0. *, **, *** shows the statistical significance of test statistic and coefficient at 10%, 5%, 1%.

Comparisons among AB, BB1 and BB2 estimations show that temperature and oil price volatility variables do not have significant effects on electricity consumption. We obtain statistically significant and correctly signed coefficients on lnpcgdp and lnrep variables. Significance and sign of coefficient on uratio variable vary according to the estimation method employed. We find that electricity consumption is inelastic with respect to income and price. 1% increase in income (electricity price) leads an 0.34% (0.11%) increase (decrease) in electricity consumption.

7.3.5. Estimation Results for the Dynamic Panel Data Model with h5_nexcr

Table 7.15 presents the estimation results of dynamic panel data model. Good estimates of the true parameter on $lnpcec_{-1}$ lie between 0.679109 and 0.946563. In order to deal with the problem of dynamic panel bias present in OLS and within estimation, we estimate the model by Balestra and Nerlove (1966) (BN1 and BN2), Anderson and Hsiao (1981 and 1982) (AH1 and AH2), Arellano-Bond (1991) (AB), Blundell and Bond (1998) (BB1 and BB2) estimation methods.

There is evidence of misspecification in the model for BN1 and BN2 estimations. In other five estimations, all the diagnostic tests indicate that the model is correctly specified. We find that although signs of coefficients on cdd and h5_nexcr depend on the estimation method, statistical insignificance of these coefficients is a common result among the estimations and hdd has significant impact on lnpcec in only AH1 and AH2 estimations at 8% significance level. Coefficients on lnpcgdp, lnrep, uratio variables are highly significant and signs are in line with the theoretical expectations in AB and BB2 estimations. But they are all insignificant in AH2 estimation.

In BB2 estimation, different from BB1, taking into account possible correlation between fixed effects and $lnpcec_{-1}$, lnpcgdp, lnrep, uratio, hdd and cdd variables lead to some changes in the results with comparison to BB1 estimation such as, signs of coefficients on cdd and h5_nexcr, statistical significance and magnitude of coefficient on uratio and magnitude of coefficients on $lnpcec_{-1}$, lnpcgdp and lnrep show some difference between these two estimations. Estimates of coefficients from BB2 estimation reveal that electricity consumption is inelastic with respect to income and price. We estimate the dynamic panel data model by using the cross sectional demeaned series because of cross sectional dependency problem and Table 7.16 shows the estimation results. We obtain similar results and Pesaran (2004) cross sectional dependence test show that the degree of the cross sectional dependency diminishes.

Table 7.15 Alternative Estimates of Dynamic Panel Data Model with h5_nexcr, Number of Groups=65

lnpcec\Methods	**OLS**	**WITHIN**	**AB**	**BB1**	**BB2**
lnpcec $_{-1}$	0.947*** (0.000)	0.679*** (0.000)	0.496*** (0.000)	0.857*** (0.000)	0.499*** (0.000)
lnpcgdp	0.073*** (0.000)	0.225*** (0.000)	0.383*** (0.000)	0.213*** (0.009)	0.387*** (0.000)
lnrep	-0.056 (0.177)	-0.061 (0.203)	-0.153*** (0.002)	-0.089* (0.067)	-0.156*** (0.001)
uratio	-0.022 (0.552)	1.515*** (0.000)	2.934*** (0.000)	0.015 (0.896)	2.904*** (0.000)
hdd	1.18E-05 (0.104)	4.91E-06 (0.808)	2.54E-05 (0.208)	1.91E-05 (0.303)	2.58E-05 (0.194)
cdd	2.54E-05 (0.246)	6.15E-05 (0.441)	-6.7E-05 (0.465)	4.04E-05 (0.355)	-7.3E-05 (0.427)
h5_nexcr	-40.85*** (0.008)	-19.82 (0.253)	19.656 (0.426)	-11.37 (0.615)	21.161 (0.373)
constant	-0.25176 (0.332)	-0.015 (0.970)	-	-0.537 (0.261)	-0.889 (0.137)
Hansen J Test Statistic	-	-	56.46 (0.188)	56.49 (0.162)	56.36 (0.191)
AB Test – 1	-1.38 (0.1661)	-0.12 (0.9033)	-3.5*** (0.0000)	-4.13*** (0.0000)	-3.55*** (0.0000)
AB Test - 2	-0.6 (0.5456)	-0.87 (0.3869)	0.43 (0.6670)	-0.27 (0.7830)	0.44 (0.6630)
AB Test - 3	1.56 (0.1187)	0.09 (0.9306)	1.59 (0.1110)	1.95* (0.0520)	1.57 (0.1150)
Instruments #	-	-	55	55	56
Pesaran CD Test	5.68*** (0.000)	5.41*** (0.000)	1.71*** (0.088)	5.63*** (0.000)	2.13** (0.033)

Notes: P-values are in parentheses. Hansen J statistic for testing the validity of instruments is asymptotically χ^2 distributed with d.f.=overidentification degrees which are 48, 47 and 48 in AB, BB1 and BB2, respectively. AB(1), AB(2) and AB(3) tests are the first, second and third order autocorrelation tests developed by Arellano and Bond (1991) and asymptotically N(0,1) under H_0. *, **, *** shows the statistical significance of coefficient and test statistic at 10%, 5%, 1%.

Table 7.16 System GMM Estimation Results of Dynamic Panel Data Model with h5_nexcr and cross sectional demeaned series, Number of Groups=65

lnpcec*\Methods	**BB2**	
lnpcec*$_{-1}$	0.5745179	(0.000)***
lnpcgdp*	0.4274584	(0.003)***
lnrep*	-0.5914244	(0.069)*
uratio*	1.380784	(0.040)**
hdd*	0.000012	(0.727)
cdd*	-2.72E-06	(0.981)
h5_nexcr	-6.590933	(0.649)
constant	0.0003842	(0.991)
Hansen J Test Statistic	45.13	(0.142)
AB Test – 1	-3.20	(0.001)***
AB Test - 2	-0.15	(0.883)
AB Test - 3	1.73	(0.084)*
Instruments #	44	
Pesaran CD test	-1.98	(0.047)**

Notes: P-values are in parentheses. Hansen J statistic for testing the validity of instruments is asymptotically χ^2 distributed with d.f.=overidentification degree. Overidentification degree is 36. AB(1), AB(2) and AB(3) tests are the first, second and third order autocorrelation tests developed by Arellano and Bond (1991) and asymptotically N(0,1) under H_0. *, **, *** shows the statistical significance of test statistic and coefficient at 10%, 5%, 1%.

7.3.6. Estimation Results for the Dynamic Panel Data Model with h6_ise100

We perform estimation of dynamic panel data model employing different estimation methods. Results of some estimations are in Table 7.17. From within and OLS estimation, we find the interval of good parameter estimates for the coefficient on lnpcec$_{-1}$ as (0.944529, 0.680762).

In BN1, BN2, AH1, AH2, AB, BB1 and BB2 estimations, we take into account dynamic panel bias problem associated with the inclusion of lnpcec$_{-1}$ into the model in OLS and within estimations. Diagnostic tests show that except for BN1 estimation, there is no evidence of misspecification.

Table 7.17 Alternative Estimates of Dynamic Panel Data Model with h6_ise100, Number of Groups=65

lnpcec\Methods	**OLS**	**WITHIN**	**AB**	**BB1**	**BB2**
$lnpcec_{-1}$	0.945*** (0.000)	0.681*** (0.000)	0.497*** (0.000)	0.875*** (0.000)	0.502*** (0.000)
lnpcgdp	0.081*** (0.000)	0.238*** (0.000)	0.3228*** (0.000)	0.199*** (0.002)	0.326*** (0.000)
lnrep	-0.073 (0.101)	-0.069 (0.128)	-0.107** (0.025)	-0.098** (0.040)	-0.110** (0.023)
uratio	-0.025 (0.517)	1.542*** (0.000)	3.134*** (0.000)	-0.040 (0.598)	3.129*** (0.000)
hdd	1.47E-05** (0.040)	1.28E-05 (0.507)	1.86E-05 (0.292)	2.41E-05* (0.052)	1.92E-05 (0.283)
cdd	3.08E-05 (0.161)	0.00007 (0.409)	-4.1E-05 (0.686)	5.04E-05 (0.169)	-5.1E-05 (0.616)
h6_ise100	-0.921 (0.118)	-0.599 (0.313)	-0.4459 (0.491)	-0.442 (0.509)	-0.371 (0.555)
constant	-0.378 (0.172)	-0.16113 (0.642)	-	-0.625* (0.066)	-0.454 (0.379)
Hansen J Test Statistic	-	-	56.93 (0.177)	56.16 (0.169)	57.14 (0.172)
AB Test – 1	-1.16 (0.2476)	-0.02 (0.9852)	-3.55*** (0.000)	-4.14*** (0.000)	-3.48*** (0.001)
AB Test - 2	-0.48 (0.6283)	-0.81 (0.4208)	0.35 (0.728)	-0.33 (0.740)	0.38 (0.703)
AB Test - 3	1.56 (0.1178)	0.09 (0.9263)	1.82* (0.069)	1.98** (0.048)	1.79* (0.073)
Instruments #	-	-	55	55	56
Pesaran CD Test	8.13*** (0.000)	4.66*** (0.000)	0.94 (0.348)	6.30*** (0.000)	1.82* (0.069)

Notes: P-values are in parentheses. Hansen J statistic for testing the validity of instruments is asymptotically χ^2 distributed with d.f.=overidentification degree. Overidentification degrees are 48, 47 and 48 in AB, BB1 and BB2, respectively. AB(1), AB(2) and AB(3) tests are the first, second and third order autocorrelation tests developed by Arellano and Bond (1991) and asymptotically N(0,1) under H_0. *, **, *** shows the statistical significance of coefficient and test statistic at 10%, 5%, 1%.

According to the estimation results, hdd and cdd do not have significant contributions to explain the changes in lnpcec at 5% significance level. Positive and significant coefficient on lnpcgdp is observed in AH1, AB, BB1 and BB2 estimations. We find that lnrep has significant and negative effect on lnpcec in all the estimations except BN2 estimation; however, the reverse is true for h6_ise100 such that its negative and significant impact is observed only in BN2 estimation. Estimations again give mixed results for the significance and sign of the coefficient on uratio. We obtain satisfactory results related to its sign and significance simultaneously in BN2, AB and BB2 estimations.

Minor changes in signs, significance and magnitudes of coefficients occur when we remove lnpcec$_{-1}$, lnpcgdp, lnrep, uratio, hdd and cdd variables from the levels equation in BB2 estimation. We can conclude that electricity consumption is inelastic with respect to income and price.

Table 7.18 System GMM Estimation Results of Dynamic Panel Data Model with h6_ise100 and cross sectional demeaned series, Number of Groups=65

lnpcec*\Methods	**BB2**	
lnpcec*$_{-1}$	0.5745179	(0.000)***
lnpcgdp*	0.4274584	(0.003)***
lnrep*	-0.5914244	(0.069)*
uratio*	1.380784	(0.039)**
hdd*	0.000012	(0.727)
cdd*	-2.72E-06	(0.981)
h6_ise100	-0.4175889	(0.440)
constant	0.0058499	(0.870)
Hansen J Test Statistic	45.13	(0.142)
AB Test – 1	-3.20	(0.001)***
AB Test - 2	-0.14	(0.885)
AB Test - 3	1.73	(0.083)*
Instruments #	44	
Pesaran CD test	-1.70	(0.090)*

Notes: P-values are in parentheses. Hansen J statistic for testing the validity of instruments is asymptotically χ^2 distributed with d.f.=overidentification degree. Overidentification degree is 36. AB(1), AB(2) and AB(3) tests are the first, second and third order autocorrelation tests developed by Arellano and Bond (1991) and asymptotically N(0,1) under H_0. *, **, *** shows the statistical significance of test statistic and coefficient at 10%, 5%, 1%.

As there is cross sectional dependency problem, the estimation of dynamic panel data model was performed by employing the cross sectional demeaned series. We present the estimation results in Table 7.18. Similar results are obtained and the degree of the cross sectional dependency diminishes as indicated by Pesaran (2004) cross sectional dependence test.

As a summary, when we compare the results obtained from the estimations of dynamic panel data model employing different volatility variables based on Blundell and Bond (1998) method (BB2) which is more stable and efficient compared to AB "difference" GMM estimation, we observe that only the industrial production volatility has significant effect on the electricity consumption whether or not we consider cross-sectional dependency. Our results are robust to the use of different volatility variables as electricity demand is inelastic with respect to income and price in all the estimations. In Chapter 9, we provide comparison of our results with the previous studies.

The same electricity demand model without weather variables is estimated for the panel of OECD countries including only the oil price volatility as a measure of economic volatility in Section 8.

CHAPTER 8

PANEL DATA APPLICATION TO OECD COUNTRIES

In this section, we analyze the factors that affects electricity consumption for OECD countries. First, in section 8.1, we examine the available data and give information about data sources. Section 8.2, 8.3 and 8.4 are devoted to unit root, cointegration and poolability tests. In section 8.5, we present the static pooled and fixed effects estimation results and diagnostic tests. We discuss the findings from the estimations of dynamic panel data model using various methods in section 8.6. At last, Section 8.7 and 8.8 present the estimation results of cointegration relation and error correction model in panel data context.

8.1. Data

We use annual balanced panel data on 27 OECD countries (namely, Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Korea, Rep., Luxembourg, Mexico, Netherlands, New Zealand, Norway, Portugal, Slovak Republic, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States) over the period from 1985 to 2007. Data set includes per capita electricity consumption (pcec), per capita gross domestic product (pcgdp), real index for electricity end use price (rep), urbanization ratio (uratio) and conditional variance of crude oil price growth used as a proxy for economic volatility (oil price volatility) (h4_poil). We obtain per capita electricity consumption (kWh per capita) and real index for electricity end use price (2005=100) data from the International Energy Agency Database. Data on per capita gross domestic product, PPP (constant 2005 international $) and urbanization ratio (%) are from World Bank World Development Indicators and Global Development Finance Database. We calculated conditional variance of crude oil price growth in Section 5. According to Databases, definitions of variables are as follows;

-“per capita electricity consumption is the production of power plants excluding own use by plant and transmission, distribution and transformation losses in terms of per capita” (IEA, 2010);
- “per capita gross domestic product, PPP (constant 2005 international $) is GDP per capita based on purchasing power parity, i.e. converted to international dollars by use of PPP rates” (World Bank, 2011).

> GDP at purchaser's prices is the sum of gross value added by all resident producers including product taxes and excluding any subsidies not included in the value of the products. It is assumed that there is no any depreciation of assets or depletion and degradation in natural resources (World Bank, 2011);

-real index of electricity end-use prices for industry and households (2005=100) are calculated from nominal end-use prices. They use Paasche formula in derivations. Country specific producer and consumer price indices (2005=100) are employed for the deflation of nominal prices to calculate real price index. “Nominal end-use prices are prices actually paid including transaction costs and taxes which are not refundable. Annual data are twelve-month averages” (IEA, 2010: 6).
-“urbanization is the percentage of urban population in total population” (World Bank, 2011);

In the analysis, natural logarithms of per capita electricity consumption, per capita gross domestic product and real index for electricity end use price series are employed. Summary statistics are given in Table 8.1. Between standard deviation of h4_poil is zero as it is country invariant. As mentioned by Baum (2006), small within standard deviation like in the cases of uratio and h4_poil, indicate that coefficients on these variables may not be well identified in fixed effects model estimation. For all the variables except h4_poil, variations across countries are greater than the variation over time; this can lead to huge efficiency loss in within estimation, this situation is emphasized by Cameron and Trivedi (2009).

Table 8.1 Summary Statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
pcec	overall	7878.281	5197.678	632.029	25594.9	N=621
	between		5199.161	1297.748	23925.51	n=27
	within		971.4736	4247.676	11915.13	T=23
pcgdp	overall	25409.08	9961.287	6497.95	74421.6	N=621
	between		9061.435	8768.932	52031.44	n=27
	within		4475.622	4331.231	47799.23	T=23
rep	overall	100.885	22.19659	41.1738	185.556	N=621
	between		17.0781	76.78836	128.5809	n=27
	within		14.53878	60.91784	159.3482	T=23
lnpcec	overall	8.754626	0.694999	6.448935	10.15015	N=621
	between		0.681174	7.104873	10.08182	n=27
	within		0.188389	7.699229	9.546767	T=23
lnpcgdp	overall	10.06091	0.422989	8.779242	11.2175	N=621
	between		0.395255	9.066383	10.83097	n=27
	within		0.168038	9.367833	10.60415	T=23
lnrep	overall	4.59054	0.216333	3.717801	5.223354	N=621
	between		0.1688	4.319057	4.839966	n=27
	within		0.138988	3.933239	5.011298	T=23
uratio	overall	0.72996	0.110812	0.453	0.9734	N=621
	between		0.11082	0.518591	0.967722	n=27
	within		0.020836	0.614891	0.806143	T=23
h4_poil	overall	0.008151	0.004171	0.003108	0.024414	N=621
	between		0	0.008151	0.008151	n=27
	within		0.004171	0.003108	0.024414	T=23

Notes: lnpcec=ln(pcec), lnpcgdp=ln(pcgdp), lnrep=ln(rep), Variation over time (across countries) is defined by within (between) variation. Overall variance is decomposed as within and between variance. Minimum and maximum of panel series are given by columns min and max for overall (x_{it}), between ($\bar{x}_i$) and within ($x_{it} - \bar{x}_i + \bar{x}$). N is the total number of observations, n shows the number of countries. T is the time series dimension for each country.

Table 8.2 Correlation Matrix

Variables	lnpcec	lnpcgdp	lnrep	uratio	h4_poil
lnpcec	1.000000				
lnpcgdp	0.818505	1.000000			
lnrep	-0.201714	-0.019200	1.000000		
uratio	0.417873	0.444213	-0.082138	1.000000	
h4_poil	-0.009315	-0.001653	0.012632	-0.009673	1.000000

Table 8.2 shows the pairwise correlations among the variables. There is strong and positive correlation between lnpcec and lnpcgdp as we expect. And also, we observe that the correlations of lnpcec with other variables are less than 0.5 and signs of correlations are in line with a priori expectations. Correlations between independent variables are less than 0.5 implying that there is no serious collinearity problem among the variables included as explanatory variables.

Figure A.12-A.16 display time series graphs of each variable for each country. We observe significant differences in time patterns across countries. For Canada, Denmark, Germany, Hungary, Luxembourg, New Zealand, Norway, Slovak Rep., Sweden, Switzerland, lnpcec series has a cyclical pattern and for other countries it has an increasing trend. Among this countries, cyclical pattern in Norway can be explained by the extensive use of electricity for heating and therefore its sensitivity to weather conditions as also mentioned by Bernstein and Madlener (2011). Seven countries, Finland, Hungary, Mexico, New Zealand, Slovak Rep., Sweden and Switzerland show cyclical pattern in their lnpcgdp series and we observe increasing trend for other countries. Luxembourg has the highest level throughout the period. In the lnrep series, Japan’s sharp decreasing trend is very much interesting. Bernstein and Madlener (2011) have attributed this situation as a result of sharp decline in oil price decreasing the costs of the electricity sector with high oil proportion in its generation mix and also they have asserted another possible reason to be the effects of energy policies on price decline. In all the countries, urbanization increases over time as a result of development. Belgium has the highest urbanization ratio begins at 0.95 in 1985 and increase to 0.97 in 2007. Oil price volatility series reach its peak at 0.024 in 1986 which may be due to oil price collapse resulted from disagreement among OPEC countries as discussed by Jones and Leiby (1996). After 1986, volatility becomes very much erratic. Also, Sauter and Awerbuch (2003) find that oil prices volatility increases after 1986 from the examination of the existing literature.

8.2. Unit Root Tests

In this section, we perform unit root tests for each variable in our model. We begin unit root testing with the oil price volatility employing time series unit root tests as this variable is invariant with respect to cross-sectional dimension. And for other variables, we use panel unit root testing procedures.

8.2.1. Unit Root Test for Volatility Variable

Table 8.3 shows the results of unit root tests for oil price volatility variable in terms of level and first differenced forms of series. For ADF, Elliott-Rothenberg-Stock DF-GLS, Phillips-Perron, Elliott-Rothenberg-Stock, Ng-Perron and Ziwot-Andrews tests, we reject the null hypothesis of unit root at most 10% level; on the other hand, KPSS leads us to the same conclusion by not rejecting the null hypothesis of stationarity. So, we can conclude that oil price volatility series is I(0). Breaks in 1988, 1989 and 1991 can be as result of oil price collapse in 1986 and Gulf War between 1990 and 1991.

Table 8.3 Unit Root Tests for Volatility Variable

Tests /Series	h4_poil			
	Level		**First Difference**	
Augmented Dickey-Fuller test	-5.129886*** (0.0005)		-12.20083*** (0.0000)	
Elliott-Rothenberg-Stock DF-GLS test	-4.687209***		-0.279923	
Phillips-Perron test	-5.093329*** (0.0005)		-12.20083*** (0.0000)	
Kwiatkowski-Phillips-Schmidt-Shin test	0.095049		0.500000	
Elliott-Rothenberg-Stock test	3.008051*		30.13972	
Ng-Perron test				
MZa	-10.6235**		0.05782	
MZt	-2.30382**		0.16374	
MSB	0.21686**		2.83167	
MPT	2.30967**		405.778	
Ziwot and Andrews Test	**Statistic**	**Break**	**Statistic**	**Break**
1. Break in intercept (A)	-8.458134***	1988	-17.86259***	1989
2. Break in trend (B)	-9.307858***	1989	-15.20832***	1991
3. Break in intercept and trend (C)	-8.213358***	1989	-15.09690***	1991

Note: The null hypothesis is that the series is a unit root process except for Kwiatkowski-Phillips-Schmidt-Shin test. An intercept is included in the test equations. P-values are provided in parentheses.The lag length was selected by using the Schwarz Information Criteria. For Newey-West bandwidth selection, Bartlett kernel was used. Elliott-Rothenberg-Stock DF-GLS test critical values for level (differenced) series 1%, 5% and 10% significance levels are -2.674290 (-2.708094), -1.957204 (-1.962813) and -1.608175 (-1.606129), respectively. Asymptotic critical values of KPSS test at 1%, 5% and 10% significance levels are given as 0.739, 0.463 and 0.347, respectively. 1.87, 2.97 and 3.91 are the critical values of Elliott-Rothenberg-Stock test at 1%, 5% and 10% significance levels, respectively. Asymptotic critical values of Ng-Perron test are -13.8, -8.1 and -5.7 for Mza statistics; -2.58, -1.98, -1.62 for MZt statistics; 0.174, 0.233, 0.275 for MSB statistics; and 1.78, 3.17 and 4.45 for MPT statistics at 1%, 5% and 10% significance levels, respectively. The critical values for Zivot and Andrews test for model A are -5.34, -4.80 and -4.58; for model B are -4.93, -4.42 and -4.11; and for model C are -5.57,-5.30 and -4.82 at 1%, 5% and 10% levels of significance respectively.

*, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%.

8.2.2. Panel Unit Root Tests

In order to determine the stationarity properties of panel series, we perform panel unit root tests. As already mentioned in Chapter 6, there are two groups of tests based on the assumption of the cross sectional dependence. The first group of tests are called first generation panel unit root tests and based on the assumption of cross sectional independence. However, as shown by O'Connell (1998), in the presence of cross-sectional dependence, the first generation tests tend to overreject the null hypothesis of unit root. Therefore, we need to check if there exists cross-sectional dependence problem in the panel series before applying the panel unit root tests. Table 8.4 shows the results of cross-sectional dependence test. In the table, Pesaran (2004) Cross section dependence (CD) test given by the equation (8.1) is based on the estimated correlation coefficients between time series for each cross section i and j ($\hat{\rho}_{ij}$).

$$CD = \left[\sqrt{\frac{2}{N(N-1)}}\right] \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \sqrt{T_{ij} * \hat{\rho}_{ij}} \tag{8.1}$$

We can conclude that there exists cross-sectional dependence problem in all the series. Cross-sectional dependence can be corrected to some extent by subtracting cross-sectional means from each series and then applying first generation panel unit root tests to demeaned series as suggested by Hsiao (1986), Levin et al. (2002), Im et al. (2003). However, as we cannot eliminate the problem of cross-sectional dependence totally by this procedure, we prefer to use second generation panel unit root tests. The results are given in Tables 8.5, 8.6, 8.7, and 8.8. Table 8.5 shows the results of Pesaran (2006)'s CADF unit root test results. In table, we present the results of unit root tests for each country (CADF statistic) and also for panel as a whole by taking the averages of countries' CADF statistics (CIPS statistic).

Table 8.4 Pesaran (2004) CD Test for Cross Section Dependence

	CD-test	p-value	Corr[1]	abs(corr)[2]
lnpcec	63.93***	0.000	0.711	0.735
lnpcgdp	82.15***	0.000	0.914	0.914
lnrep	5.62***	0.000	0.063	0.509
uratio	74.52***	0.000	0.829	0.831

Note: Under the null hypothesis of cross-section independence, CD ~ N(0,1) for large N and $T_{ij} \geq 3$; *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%.

[1]Averaged correlation coefficient

[2] Averaged absolute correlation coefficient

Based on CADF statistics, test fails to reject the null hypothesis of a unit root in electricity consumption series for the countries except Australia, Finland, Portugal and U.K. The null of nonstationarity for income series is rejected only for Norway at 10% level of significance. Electricity price series is found to be stationary for Finland, France, Germany, Italy and Portugal. Test indicates that urbanization ratio series of Mexico and U.K. is stationary at %5 and %10 significance levels, respectively. According to CIPS statistics, all the panel series are nonstationary.

Therefore, in order to determine whether or not the series are I(1), we perform CADF unit root test to the first differenced series. Table 8.6 shows the results of CADF tests for the series in first differences. Test results indicate that first differenced electricity consumption series of Australia, Belgium, Denmark, Finland, Greece, Korea, Mexico, New Zealand, Norway, Slovak Republic, Sweden, Switzerland, United Kingdom, United States; first differenced income series of Australia, Belgium, Germany, Greece, Hungary, Italy, Luxembourg, Turkey; first differenced electricity price series of Australia, Belgium, France, Portugal, Sweden, United States; first differenced urbanization ratio series of Belgium are stationary. We found that all the panel series except urbanization ratio are I(1).

Table 8.5 Pesaran (2006) CADF Tests Results for Series in Levels

Series/Countries	lnpcec		lnpcgdp		lnrep		uratio	
	CADF	**p**	**CADF**	**p**	**CADF**	**p**	**CADF**	**p**
Australia	-3.805*	1	-1.951	1	-2.739	1	-1.7380	1
Austria	-0.4456	4	-2.077	2	-1.835	2	0.0012	1
Belgium	-0.805	3	0.1972	1	-3.105	1	0.8341	1
Canada	-4.043	1	-1.721	1	-1.84	2	-1.6708	2
Denmark	-0.8194	3	-0.05588	1	-0.1576	2	0.4101	1
Finland	-3.734*	1	-0.8778	2	-3.862*	2	-1.8813	2
France	-1.047	1	-3.375	1	-4.537**	1	-0.1331	1
Germany	0.05438	4	0.2938	2	-4.451**	2	-1.6277	2
Greece	-2.231	1	-0.4701	1	-2.597	2	0.3351	1
Hungary	-0.3985	1	-0.309	1	-0.782	1	-1.6849	2
Ireland	-0.8452	1	-1.362	4	-2.299	1	-1.1017	1
Italy	-0.09926	4	-2.573	1	-3.724*	1	2.2467	1
Japan	-1.557	1	-1.064	1	-1.583	1	-2.7882	1
Korea, Rep.	-1.322	2	-0.08545	1	-0.7912	3	-0.5507	1
Luxembourg	-3.259	1	-0.3123	1	-2.627	1	-3.0251	1
Mexico	-2.412	1	-1.79	1	-1.863	1	-4.6677**	3
Netherlands	-1.389	3	-1.975	1	-2.397	1	-1.9052	1
New Zealand	-3.179	1	-0.5707	1	-3.211	4	1.3119	1
Norway	-2.728	1	-3.603*	1	-0.8935	1	0.6913	1
Portugal	-5.024***	1	-3.38	2	-3.592*	1	-2.8951	1
Slovak Rep.	-1.732	1	-2.28	1	-1.646	1	-2.8114	1
Spain	-1.933	1	-3.467	4	-3.325	2	-2.6461	1
Sweden	-2.809	1	-1.46	2	0.3558	2	-3.4478	1
Switzerland	-1.403	1	0.2057	1	-2.017	1	-3.4069	1
Turkey	-1.519	1	-0.8955	1	-3.163	1	-2.7189	1
U.K.	-8.47***	4	-1.781	1	-3.274	1	-3.5660*	3
U.S.	-1.576	1	-0.9921	1	-1.67	1	-2.8218	1
CIPS Stat	-2.168		-1.397		-2.356		-1.5281	
CIPS Stat_t[1]	-2.092		-1.374		-2.170		-1.548	

Note: The lag lengths (p) are selected according to Schwarz information criterion. Maximum lag is taken as 4 (3) for lnpcec, lnpcgdp, lnrep (uratio). An intercept and trend were included in the test equations. The critical values for the CADF test were obtained from Pesaran (2006), Table 1c as -4.69, -3.88 and -3.49 at 1%, 5% and 10% levels of significance, respectively. The critical values for the CIPS test were obtained from Pesaran (2006), Table 2c as -2.81, -2.66 and -2.58 at 1%, 5% and 10% levels of significance, respectively.
*, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%.
[1] Extreme t-values were truncated.

Table 8.6 Pesaran (2006) CADF Tests Results for Series in First Differences

Series/Countries	Δlnpcec		Δlnpcgdp		Δlnrep		Δuratio	
	CADF	**p**	**CADF**	**p**	**CADF**	**p**	**CADF**	**p**
Australia	-5.7886***	1	-3.5729*	1	-4.0736**	1	-3.1069	1
Austria	-1.5100	4	-2.7326	1	-3.1371	1	-3.2170	1
Belgium	-3.5799*	2	-4.3029**	1	-3.7046*	1	-4.4072**	2
Canada	-3.4461	1	-3.2125	1	-2.8063	2	-2.2794	1
Denmark	-3.6185*	1	-1.7169	1	0.0597	2	-2.9812	1
Finland	-4.8626***	1	-2.1345	1	-3.3838	2	-2.1637	1
France	-3.2416	1	-2.9845	1	-6.2694***	1	-0.4061	1
Germany	-2.3463	4	-4.2753**	1	-1.2950	2	-2.2232	1
Greece	-4.5119**	1	-4.3313**	1	-2.4180	1	-2.0223	1
Hungary	-2.9254	2	-3.7680*	1	-1.8979	1	-2.3395	1
Ireland	-1.6865	1	-0.9317	4	-2.4211	1	-2.6546	1
Italy	-0.0021	4	-4.3134**	1	-1.6384	3	-0.8114	1
Japan	-2.3947	1	-2.1718	1	-3.2432	1	-1.9611	1
Korea, Rep.	-4.1675**	1	-2.2205	1	-2.7014	3	-2.8174	1
Luxembourg	-2.9241	1	-4.2127**	1	-3.1600	1	-1.3620	1
Mexico	-4.8992***	1	-1.4733	1	-0.7096	1	-1.9953	1
Netherlands	-2.4314	2	-3.0978	1	-3.1272	1	-2.0108	1
New Zealand	-3.7076*	1	-1.8934	1	-1.7173	4	-2.4177	1
Norway	-5.0028***	1	-3.1117	2	-1.8087	1	-3.0204	1
Portugal	-1.7170	2	-2.8373	1	-3.6245*	1	-1.8208	1
Slovak Rep.	-5.8065***	1	-2.7161	1	-2.7262	1	-1.9877	1
Spain	-3.3093	1	-2.3960	1	-2.6821	2	-1.9181	1
Sweden	-5.0267***	1	-5.2209***	1	-3.5270*	1	-1.7157	1
Switzerland	-4.7275***	1	-2.3827	1	-2.5140	1	-1.7197	1
Turkey	-2.7261	1	-5.1717***	1	-3.2424	1	-1.5548	1
U.K.	-4.3701**	1	-3.0457	1	-3.1179	1	-0.0911	3
U.S.	-3.8174*	1	-2.8879	1	-3.5350*	1	-1.8334	1
CIPS Stat	-3.5018***		-3.0784***		-2.7564**		-2.1051	
CIPS Stat_t[1]	-3.5018***		-3.0784***		-2.7564**		-2.1051	

Note: The lag lengths (p) are selected according to Schwarz information criterion. Maximum lag is taken as 4 (3) for lnpcec, lnpcgdp, lnrep (uratio). An intercept and trend were included in the test equations. The critical values for the CADF test were obtained from Pesaran (2006), Table 1c as -4.69, -3.88 and -3.49 at 1%, 5% and 10% levels of significance, respectively. The critical values for the CIPS test were obtained from Pesaran (2006), Table 2c as -2.81, -2.66 and -2.58 at 1%, 5% and 10% levels of significance, respectively.
*, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%.
[1] Extreme t-values were truncated.

In order to check for the robustness of Pesaran (2006) panel unit root test, we perform Hadri (2000) test. Following Carrion-i-Silvestre et al. (2005), we calculate the bootstrap distributions of the statistics to deal with cross sectional dependence problem. In addition, to analyze the presence of unit roots in the series with structural breaks, we also perform PANKPSS test proposed by Carrion-i-Silvestre et al. (2005), however, as analysis of structural breaks is not our main concern, we present the results of the tests which allow structural breaks in the series in Appendix A.3. Table 8.7 and 8.8 show the results of the tests for series in level and in first differences without introducing structural breaks and under the assumptions of cross-sectional dependence and independence.

Table 8.7 Hadri (2000) Panel Unit Root Test Results for Series in Levels

PANEL DATA TESTS					
Series		**lnpcec**	**lnpcgdp**	**lnrep**	**uratio**
Homogeneous variance		4.797 (0.000)	21.245 (0.000)	4.298 (0.000)	133.824 (0.000)
B.C.V.	10%	10.053	13.396	10.125	22.940
	5%	11.706	16.868	11.744	31.909
	1%	15.010	25.027	15.316	53.245
Heterogeneous variance		23.402 (0.000)	36.185 (0.000)	17.582 (0.000)	109.762 (0.000)
B.C.V.	10%	24.983	26.518	24.478	32.218
	5%	29.715	32.273	28.966	43.155
	1%	42.172	49.667	38.877	73.186

Note: The long-run variance is estimated using Bartlett spectral kernel with automatic spectral window bandwidth selection. 2,000 replications are performed in the bootstrap distribution. Asymptotic P values obtained under the assumption of no cross-sectional dependence are provided in parentheses. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%. B.C.V. is abbreviation for Bootstrap Critical Values

Statistics are computed for both assumptions of homogeneous and heterogeneous long run variance estimates. Under the assumption of cross-sectional independence, null hypothesis of stationarity for all the series in levels is rejected. But the consideration of the cross-sectional dependence of the statistics leads to different conclusions. For electricity consumption and electricity price series, regardless of the homogeneity assumption on long run variance estimate, test shows that the series is stationary. The test indicate that income and urbanization ratio series is nonstationary at 5% and 1% significance levels, respectively, both under the homogeneous and heterogeneous long run variance.

Table 8.8 Hadri (2000) Panel Unit Root Test Results for Series in First Differences

PANEL DATA TESTS					
Series		**Δlnpcec**	**Δlnpcgdp**	**Δlnrep**	**Δuratio**
Homogeneous variance		9.589 (0.000)	3.908 (0.000)	-0.330 (0.629)	-0.857 (0.804)
B.C.V.	10%	10.12	10.673	10.762	22.297
	5%	11.56	12.344	12.509	32.351
	1%	14.338	16.609	16.952	58.018
Heterogeneous variance		18.032 (0.000)	12.859 (0.000)	13.710 (0.000)	25.419 (0.000)
B.C.V.	10%	26.364	28.495	26.639	37.111
	5%	30.444	33.873	30.619	48.989
	1%	40.306	51.018	39.972	86.178

Note: The long-run variance is estimated using Bartlett spectral kernel with automatic spectral window bandwidth selection. 2,000 replications are performed in the bootstrap distribution. Asymptotic P values obtained under the assumption of no cross-sectional dependence are provided in parentheses. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%. B.C.V. is abbreviation for Bootstrap Critical Values

From the results of the tests for series in first differences concerning cross-sectional dependence of the statistics, we can infer that the first differenced series under consideration is stationary both under the assumption of homogeneous and heterogeneous long run variance.

In order to determine the integration order of series, we perform several unit root tests. As can be seen, based on unit root tests and various assumptions, we reach conflicting conclusions for the integration order of series. We sum up all the conclusions from different tests in Table 8.9. For comparison purposes, we present the results drawn from first generation panel unit root tests assuming cross-sectional independence of the series, in addition, results from panel unit root tests allowing for structural breaks in the series. Detailed results of these tests are given in Appendices A.2 and A.3. We continue our analysis treating all the panel series as if they are I(1).

Table 8.9 Integration Order of Series Based on Various Unit Root Tests

Series/Tests	**lnpcec**	**lnpcgdp**	**lnrep**	**uratio**
LLC	I(1)	I(0)	I(1)	I(1)
Breitung	I(p>1)	I(1)	I(1)	I(0)
IPS	I(1)	I(0)	I(1)	I(0)
ADF - Fisher	I(p>1)	I(0)	I(0)	I(0)
PP- Fisher	I(p>1)	I(0)	I(0)	I(0)
ADF - Choi	I(1)	I(0)	I(1)	I(0)
PP - Choi	I(1)	I(1)	I(1)	I(p>1)
Hadri Z-stat	I(p>1)	I(p>1)	I(p>1)	I(p>1)
Heteroscedastic Consistent Z-stat	I(p>1)	I(p>1)	I(p>1)	I(p>1)
CADF	I(1)	I(1)	I(1)	I(p>1)
PANKPSS without break				
Homogeneous	I(p>1)	I(p>1)	I(1)	I(1)
Heterogeneous	I(p>1)	I(p>1)	I(p>1)	I(p>1)
Homogeneous-CD	I(0)	I(1)	I(0)	I(1)
Heterogeneous-CD	I(0)	I(1)	I(0)	I(1)
PANKPSS with break				
Homogeneous	I(p>1)	I(p>1)	I(1)	-
Heterogeneous	I(p>1)	I(p>1)	I(p>1)	-
Homogeneous-CD	I(1)	I(0)	I(0)	I(0)
Heterogeneous-CD	I(0)	I(0)	I(0)	-

Note: CD means we account for cross-sectional dependence.

8.3. Panel Cointegration Tests

"Most cointegration tests may be misleading in the presence of stationary data, as they require all data to be I(1)" (Martins, 2010: 19). Therefore we exclude the oil price volatility from the cointegration relation. In this section, we explore the existence of long run relationship between electricity consumption, income, electricity price, and urbanization ratio which all are assumed to be I(1). In order to do this, we implement Pedroni (1999, 2004) residual-based cointegration test, Kao (1999) residual-based cointegration test, Combined Individual panel cointegration test (Fisher/Johansen), Westerlund (2006) panel LM cointegration test and Westerlund (2007) error correction-based cointegration test. The ignorance of cross-sectional dependence can cause misleading conclusions such that tests can indicate cointegration, in fact there is no. As we have shown that there is cross-sectional dependence in the panel series by Pesaran (2004) CD tests, we continue cointegration analysis with tests that considers cross-sectional dependence such as Westerlund (2006) residual-based panel LM cointegration test and Westerlund (2007) error correction-based cointegration test. Table 8.10 and 8.11 show the results. As cross section dimension is larger than the time series dimension, we cannot apply the tests with structural breaks in deterministic components. For comparison purposes, we present the results of the Pedroni (1999, 2004) residual-based cointegration test, Kao (1999) residual-based cointegration test, and Combined Individual panel cointegration test (Fisher/Johansen) which all assume cross-sectional independence in Appendix A.3.

Westerlund (2006) residual-based panel LM test indicates the evidence of cointegration between four variables, independent of the specification of deterministic terms in the test equation. We can say that all the countries of the panel are cointegrated. On the other hand, the results of Westerlund (2007) error correction-based cointegration test depends on the assumption related to correlations among cross-sectional units and test statistics employed. When we assume cross-sectional independence and also that error correction coefficient differs across countries, according to G_τ (group mean) statistics, we reject the null of no cointegration using the test equation with either intercept or the one with both intercept and trend in the test equation. This implies the evidence of cointegration between variables for at least one country. In addition, under the assumptions of cross-sectional independence and the same error correction coefficient across countries, P_τ (panel) statistics give the similar result by employing the test equations with the same deterministic terms specification and indicate the presence of cointegration for the panel as a whole at most 10% significance level. If the assumption of cross-sectional independence is violated, according to all the statistics under all the deterministic term specifications, we cannot reject null of no cointegration.

Table 8.10 Westerlund (2006) Residual-based Panel LM Cointegration Test[1]

Deterministic Terms	Only intercept	Intercept+trend
LM Statistic Value	-1.844	-1.850
	(0.967)[a]	(0.968)[a]
	(1.000)[b]	(0.902)[b]

Note: Barlett kernel window width is set according to $(4*(T/100)^{2/9})$. P-values are provided in parentheses. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%.
[a]The p-value is based on the asymptotic normal distribution.
[b]The p-value is based on the bootstrapped distribution.The number of replications is 500 in bootstraps.
[1]The null hypothesis is that there is cointegration. Test equation is estimated by Fully modified least squares. The first stage cointegration regressions with intercept only and with intercept and trend estimated by FMOLS group mean method are given as below, respectively;

$$\widehat{lnpcec}_{it} = 1.91 + 0.57 * lnpcgdp_{it} - 0.05 * lnrep_{it} + 1.78 * uratio_{it}$$
$$\widehat{lnpcec}_{it} = 0.02 + 7.73 * t + 0.27 * lnpcgdp_{it} - 0.05 * lnrep_{it} - 2.49 * uratio_{it}$$

Table 8.11 Westerlund (2007) Error Correction-based Cointegration Test[1]

		No deterministic component[2]	Only intercept	Intercept+trend
G_τ	Value	-1.665	-3.479	-4.094
	Z-Value	0.226	-6.867	-8.291
		(0.589)[a]	(0.000)[a]***	(0.000)[a]***
		(0.688)[b]	(0.688)[b]	(0.614)[b]
G_α	Value	-1.722	-1.154	-2.658
	Z-Value	5.065	7.248	8.322
		(1.000)[a]	(1.000)[a]	(1.000)[a]
		(0.456)[b]	(0.902)[b]	(1.000)[b]
P_τ	Value	-7.539	-11.340	-18.003
	Z-Value	-0.531	-1.287	-5.529
		(0.298)[a]	(0.099)[a]*	(0.000)[a]***
		(0.980)[b]	(0.982)[b]	(0.966)[b]
P_α	Value	-4.413	-4.147	-7.414
	Z-Value	-0.118	2.626	3.243
		(0.453)[a]	(0.996)[a]	(0.999)[a]
		(0.980)[b]	(0.982)[b]	(0.996)[b]

Note: Barlett kernel window width is set according to $(4*(T/100)^{2/9})$. P-values are provided in parentheses.

[a]The p-value is based on the asymptotic normal distribution.

[b]The p-value is based on the bootstrapped distribution.The number of replications is 500 in bootstraps.

[1]The null hypothesis is that there is no cointegration. Leads are included to overcome the problem of correlation between regressors and residuals of ECM due to the violation of strict exogeneity of regressors causing the tests to be dependent on the nuisance parameters. Numbers of lags and leads are chosen according to AIC for each country. Mean group DOLS estimations of long run relations are given by;

$$\widehat{lnpcec}_{it} = 4.311 * lnpcgdp_{it} - 2.558 * lnrep_{it} - 28.670 * uratio_{it}$$
$$\widehat{lnpcec}_{it} = 35.532 + 1.853 * lnpcgdp_{it} + 0.195 * lnrep_{it} - 57.455 * uratio_{it}$$
$$\widehat{lnpcec}_{it} = -1.332 + 0.0009 * t + 0.644 * lnpcgdp_{it} + 0.150 * lnrep_{it} + 1.698 * uratio_{it}$$

[2]Results change by varying the maximum lag and lead length in the process of choosing lag and lead number by AIC. However, in all the cases, we cannot reject null according to Bootstrapped p-values. Under the assumption of cross-sectional independence, when the maximum lag and lead are set at 1, the null can be rejected according to G_τ, P_τ, and P_α statistics, on the other hand, when we set maximum lag at 1and lead at 2, the null can be rejected according to G_τ, and P_τ statistics. Table shows the results in which maximum lag and lead are set at 2 and 1, respectively.

*, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%.

As we have observed in the unit root testing, in the cointegration tests also, different specifications, assumptions and methods make us to reach varied conclusions regarding to the existence of cointegration among the variables. Moreover as cross-sectional dimension is a bit larger than the time dimension, “some cointegration tests (especially Westerlund’s(2007)) may have poor power properties. Low power means that the test is not able to reject the null hypothesis when the alternative is correct” (Martins, 2010: 27). However, as most of the tests indicate the presence of cointegration, we assume there is cointegration among the variables and in the next section we estimate the possible panel cointegrating equation. Lastly, we also want to point out that the results of Pedroni tests are supported by Westerlund tests to some extent.

In the next sections, for comparison purpose, we start with static pooled model and fixed effects model estimations and perform diagnostic tests. Before estimations, we perform poolability test in section 8.4.

8.4. Poolability Test across Cross-Sectional Units

We have estimated pooled model in which all the coefficients are assumed to be same across countries and years. And also to perform poolability test under the assumptions of homoscedastic, noncorrelated and normally distributed errors (to test the assumption of the pooled model), we have estimated the same model for each country, separately. The test results are given below.

$$F = \frac{(SSR_{pooled} - \sum_{i=1}^{27} SSR_i)/(27-1)*5}{(\sum_{i=1}^{27} SSR_i)/27*(23-5)} = 716.47 \text{ with p-value=0.000} \tag{8.2}$$

Panel data are not poolable with respect to cross-sectional units. So, we need to consider the heterogeneity in our data. The heterogeneity can be handled by assuming only the intercept in the model vary across cross-sections. For our case, as the sample is not generated by using a random sampling process and it is formed in the context of predefined definitions, we will assume the effects in our model if exist, are fixed. As we have time-invariant variable, we cannot apply test for poolability over time.

8.5. Estimation Results of Pooled and Fixed Effects Models

In Table 8.12, we present the estimation results of pooled and fixed effects model. We perform normality, autocorrelation, heteroscedasticity and cross-sectional dependence tests. In estimations, the signs of the coefficients are in line with theoretical expectations. However, the coefficient on oil price volatility is insignificant. According to Jarque-Bera statistic, normal distribution for residuals is rejected at conventional significance levels. Therefore, F and t tests may not have the standard asymptotic distributions. Autocorrelation and Heteroscedasticity tests indicate the presence of both autocorrelation and heteroscedasticity. To account for autocorrelation and heteroscedasticity in the pooled model, we employ FGLS estimation assuming common AR(1) coefficients for all panels estimated as -0.9618. All specification tests namely, poolability, heteroscedasticity and autocorrelation tests, show that some important variables and heterogeneity in the data can be omitted from the model. Therefore, in order to account for unobservable qualitative factors, we estimate fixed effects model.

We begin with one-way model estimation; since we have a cross section invariant variable (fixed variable across cross-sectional units) as a explanatory variable in the model, we cannot add time effects. Therefore, we test the following hypothesis for the individual effects assuming there is no time effects; $H_0 : \mu = 0 \mid \lambda = 0$ *vs.* $H_1 : \mu \neq 0 \mid \lambda = 0$. We obtain F statistics as 449.35267 with p-value=0.000. We can conclude that individual effects are significant. However, we observe autocorrelation and heteroscedasticity in the residuals as in the residuals of pooled model. Only Frees' Cross-sectional independence test strongly rejects the absence of dependence. As other two tests can have misleading results in the cases where correlations alternate in sign and thus cancel each other due to the fact that they are based on sum of residual pairwise correlation coefficients, we can rely on the result of Frees' test. If the common factors which are the cause of cross-sectional dependence are not correlated with the regressors, then only estimated standard errors will be biased, estimators remain consistent. Driscoll and Kraay (1998) standard errors can be used to correct for cross-sectional dependence. If the factors are correlated with the regressors then biased and inconsistent estimators are obtained and one needs to employ IV or Pesaran (2006) CCE estimators. Jarque-Bera statistic indicates nonnormal distribution for residuals.

As there are heteroscedasticity and autocorrelation problems, we suspect there is still omitted variables or omitted dynamics in the model. As, we have limitations in obtaining detailed data for the analysis, we try to eliminate these problems by estimating dynamic model. First, we present the FGLSDV estimation results to consider panel specific first order autocorrelation and heteroscedasticity across panels. Sign and significance of coefficients remains same, only magnitudes change.

If we compare all the estimation results of the model, we can say that according to OLS estimation of pooled model, electricity consumption is income elastic and price inelastic; on the other hand, we observe that electricity consumption is inelastic with respect to income and price in other estimations.

Table 8.12 Pooled and Fixed Effects Estimations of Electricity Consumption Model for OECD countries

lnpcec	Pooled OLS	Pooled FGLS	Fixed Effects	FGLSDV
lnpcgdp	1.301975*** (0.000)	0.8064884*** (0.000)	0.5603702*** (0.000)	0.4491891*** (0.000)
lnrep	-0.585517*** (0.000)	-0.041342* (0.061)	-0.272406*** (0.000)	-0.0856198*** (0.000)
uratio	0.3189575*** (0.000)	1.50896*** (0.000)	3.713666*** (0.000)	4.684146*** (0.000)
h4_poil	-0.867917 (0.838)	-0.2774464 (0.200)	-0.3251732 (0.387)	-0.1402694 (0.434)
constant	-1.882344*** (0.000)	-0.3149149 (0.400)	1.659102*** (0.000)	0.8778776*** (0.000)
R^2	0.7066	-	0.8081	-
JB	21.32099*** (0.000023)	-	6.331803** (0.042176)	-
LM_ρ	579.95734*** (0.000000)	-	436.20349*** (0.000000)	-
Wooldridge	36.596*** (0.000000)	-	36.596*** (0.000000)	-
AB(1)	23.90*** (0.000000)	-	20.86*** (0.000000)	-
AB(2)	23.05*** (0.000000)	-	17.98*** (0.000000)	-
LR_H	718.89*** (0.000000)	-	344.16*** (0.000000)	-
LM_H	324.6645*** (0.000000)	-	305.3515*** (0.000000)	-
Pesaran's CD	-	-	-0.544 (0.587)	-
Free's CD	-	-	8.628***	-
Friedman's CD	-	-	21.868 (0.696)	-

Notes: Driscoll and Kraay (1998) standard errors are employed for calculation of t-test statistic to correct for possible cross-sectional dependence, heteroscedasticity and autocorrelation. P-values are provided in parentheses. JB is the Jarque-Berra statistics to test the normality of standardized residuals and JB $\sim\chi_2^2$ under null hypothesis. LM_ρ is the LM statistics to test for first order autocorrelation in the residuals; $\sim\chi_1^2$ under the assumption of no autocorrelation. Wooldridge test is the first order autocorrelation test in the residuals and it is distributed as F (1, 26) under null hypothesis. AB(1) and AB(2) tests are the first and second order autocorrelation tests developed by Arellano and Bond (1991) and asymptotically normally distributed under null hypothesis. LR_H and LM_H are the heteroscedasticity tests and have asymptotic χ^2 null distribution with 26 d.f. Pesaran's, Free's and Friedman's CD tests are cross-sectional dependence tests. First one has asymptotic N(0, 1) distribution for large T and N$\longrightarrow\infty$, whereas, Friedman's test is asymptotically χ^2 distributed with 22 d.f. for fixed T and large N under the null hypothesis of cross-section independence. Critical values from Frees' Q distribution is for 10%, 5% and 1% significance levels are 0.1124, 0.1470 and 0.2129. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%.

8.6. Dynamic Panel Data Model Estimation Results

The static model is extended by adding the lagged dependent variable as an explanatory variable to the model to get rid of autocorrelation problem as follows;

$$lnpcec = \alpha_1 lnpcec_{-1} + X\alpha_2 + D_\mu \mu + \varepsilon, \tag{8.3}$$

where $X = (lnpcgdp \quad lnrep \quad uratio \quad h4\_poil)$

The above dynamic partial adjustment model can be derived by the following steps. We have built a static electricity consumption model (desired level of electricity consumption) given by the following equation under the data constraints;

$$lnpcec^* = \beta * lnpcgdp + \gamma * lnrep + \theta * uratio + \lambda * h4\_poil + \mathrm{D}_\mu \mu_* + u \tag{8.4}$$

Current electricity consumption may not adjust to the long-run equilibrium electricity consumption immediately because it may take time for the economic agents to respond to deviations from equilibrium. To allow for this, we can define a partial adjustment mechanism such that changes in natural logarithm of actual consumption is π fraction of difference between natural logarithm of desired consumption and period (t-1)'s natural logarithm of actual consumption:

$$lnpcec - lnpcec_{-1} = \pi(lnpcec^* - lnpcec_{-1}) \tag{8.5}$$

where $0 < \pi < 1$ showing the speed of adjustment. 100* π % deviations of logarithm of actual consumption from logarithm of desired consumption is eliminated in a year.

When we substitute $lnpcec^*$ from equation (8.4) into equation (8.5) and solve for $lnpcec$, we can obtain equation (8.3).

The Table 8.13 shows the some of the alternative estimations of the dynamic panel data model. In OLS estimation, we ignore the existence of fixed effects. But here, we have the problem of dynamic panel bias (Nickell (1981)). Assuming there exists fixed effects, we use within transformation approach to get rid of the fixed effects.

$$N_{\mu} lnpcec = \alpha_1 (N_{\mu} lnpcec_{-1}) + N_{\mu} X \alpha_2 + N_{\mu} \varepsilon, \tag{8.6}$$

where $X = (lnpcgdp \quad lnrep \quad uratio \quad h4\_poil)$

However, $N_{\mu} \ln pcec_{-1}$ and $N_{\mu}\varepsilon$ are asymptotically correlated (Nickell, 1981). We cannot solve the problem of dynamic panel bias; there is still correlation between the transformed lagged dependent variable and transformed error. But from OLS and within estimations of the dynamic model, we observe that the estimate of the coefficient on the lagged dependent variable lie between 0.98395 and 0.8933049. These values show the bounds for the good estimates of the true parameter as suggested by Roodman (2008).

Following Balestra and Nerlove (1966) and Sevestre and Trognon (1996), we continue with within transformation but $N_{\mu} \ln pcec_{-1}$ will be instrumented by $N_{\mu} X_{-1}$. Here, we assume all other regressors are exogenous. The estimation result (BN1) shows that the coefficient of the lagged dependent variable is outside the range of the good estimates for the true parameter. Also, according to Hansen test, overidentifying restrictions are not valid and Arellano-Bond tests indicate autocorrelation in the residuals. In addition, we assume that GDP per capita variable is endogenous in BN2 estimation; then in the same context, $N_{\mu} \ln pcgdp$ will be instrumented with $N_{\mu} \ln pcgdp_{-1}$. Still the coefficient of the lagged dependent variable is outside the range of the good estimates for the true parameter and again Hansen test cannot validate the overidentifying restrictions; thus we can say that there is misspecification in the model. So we need to improve the estimation technique.

Table 8.13 Alternative Estimates of Dynamic Panel Data Model for OECD countries

lnpcec\ Methods	**OLS**	**WITHIN**	**AB**	**BB1**	**BB2**
lnpcec $_{-1}$	0.984*** (0.000)	0.893*** (0.000)	0.782*** (0.000)	0.958*** (0.000)	0.783*** (0.000)
lnpcgdp	-0.00096 (0.872)	0.054*** (0.000)	0.091* (0.057)	0.030 (0.515)	0.094** (0.046)
lnrep	0.018*** (0.009)	-0.044*** (0.000)	-0.079*** (0.001)	-0.003 (0.894)	-0.076*** (0.001)
uratio	-0.006 (0.694)	0.148 (0.170)	0.666* (0.063)	0.005 (0.932)	0.656* (0.080)
h4_poil	0.221 (0.509)	0.077 (0.798)	-0.078 (0.826)	0.177 (0.625)	-0.045 (0.902)
constant	0.090* (0.051)	0.501*** (0.000)	-	-	0.841*** (0.008)
Hansen J Test Statistic	-	-	25.48 (0.184)	26.44 (0.190)	25.57 (0.181)
AB Test – 1	0.58 (0.5625)	-3.36*** (0.0008)	-3.21*** (0.001)	-3.31*** (0.001)	-3.21*** (0.001)
AB Test - 2	1.61 (0.1073)	-1.93* (0.054)	-0.52 (0.604)	-0.46 (0.642)	-0.51 (0.608)
AB Test - 3	3.46*** (0.0005)	0.51 (0.6087)	1.66* (0.098)	1.55 (0.122)	1.66* (0.097)
Number of instruments	-	-	25	27	26
Number of Groups	-	-	27	27	27
Pesaran CD Test	7.45*** (0.000)	4.36*** (0.000)	1.63 (0.103)	8.07*** (0.000)	1.65* (0.098)

Notes: . P-values are provided in parentheses. Hansen J Test statistic for testing the validity of instruments is asymptotically χ^2 distributed with d.f.=degree of overidentification. Degrees of overidentification are 20, 21 and 20 in AB, BB1 and BB2 estimations, respectively. AB(1), AB(2) and AB(3) tests are the first, second and third order autocorrelation tests developed by Arellano and Bond (1991) and asymptotically normally distributed under null hypothesis. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%.

Another transformation is used, namely first differencing to omit fixed effects in Anderson and Hsiao (1981, 1982) approach;

$$\Delta \text{lnpcec} = \alpha_1 \Delta \text{lnpcec}_{-1} + \Delta X \alpha_2 + \Delta \varepsilon, \quad (8.7)$$

where, $X = (lnpcgdp \quad lnrep \quad uratio \quad h4\_poil)$

But as, $E(\Delta \ln pcec_{-1} \Delta \varepsilon) \neq 0,$ we need to instrument $\Delta \ln pcec_{-1}$ by $\Delta \ln pcec_{-2}$ or $\ln pcec_{-2}$. As, higher variances are obtained using $\Delta \ln pcec_{-2}$ shown by Arrellano (1989); and also Roodman (2008) suggests that in order to maximize the sample size, it will be better to use $\ln pcec_{-2}$, we will continue by using $\ln pcec_{-2}$ as an instrument. Again, we assume that all regressors except the lagged dependent variable are exogenous (AH1). As in the previous case, we assume that GDP per capita variable is endogenous (AH2). Autocorrelation test for both AH1 and AH2 estimations show that there is no second order autocorrelation.

To increase efficiency, longer lags of dependent variable are added as instruments, but in 2SLS, this will lead huge decreases in sample size. “Holtz-Eakin, Newey and Rosen (1988) solved this problem by using GMM-style instruments” (Roodman, 2008:23). The problem here is that if we use 2SLS which is efficient under the assumption of spherical errors, we cannot account for the first order autocorrelation in the disturbances which is inevitable after first difference transformation.Therefore, we employ Feasible GMM that models the error structure more realistically in Arellano-Bond (1991) approach.

We continue with fixed effects assumption because of the reasons that we have mentioned before. We follow the Arellano-Bond Approach (AB) to improve efficiency. As mentioned by Erlat (2011), Arrellano and Bond (1991) follows the first difference transformation and improves the Anderson and Hsiao (1981, 1982) approach by including additional moment conditions that lead to the increase in the number of instruments (overidentification situation) and consideration of the differenced error variance in the estimation process, explicitly. We assume that real electricity prices which are regulated by the governments, urbanization ratio; and oil price volatility variables are exogenous. We estimate the model by two-step difference GMM to obtain consistent and asymptotically efficient estimators. The

Windmeijer (2005) finite-sample correction is employed to deal with the downward bias in the two-step standard errors. We observe that estimation results are very sensitive to the moment numbers such that in some cases, significance and signs of coefficients vary so much. In order to determine the number of moments, we follow downward testing procedure suggested by Andrews and Lu (2001). We continue until moment selection procedure find a test which does not reject null that all moment conditions are correct for the given model and we try to minimize the Hansen (1982) J-test statistic.

In the difference equation, differenced lagged dependent variable is instrumented by second lag of the dependent variable and per capita GDP variable is instrumented by its own second lag. Because of the problem of too many instruments,we use one instrument for each variable and lag distance. When we use one instrument for each time period, variable and lag distance, number of instruments exceeds the number of groups. In this case, Roodman (2008) points out that this causes the problem of too many instruments which weakens Hansen test and leads singular two-step estimated covariance matrix of moments, therefore the need to use generalized inverse in the calculation of optimal weighting matrix for two-step estimation.

Estimation results are given in Table 8.13. The sign of the all coefficients are proper to our a priori expectations. However, the negative effect of oil price volatility is insignificant. Arellano-Bond test indicates absence of second order autocorrelation. There is first order autocorrelation as we have expected. So by including dynamics into the model, we get rid of the autocorrelation problem. Another test which is related to the validity of overidentifying restrictions show that we cannot reject null hypothesis of validity of the restrictions according to the Hansen test. Therefore, tests indicate that there is no misspecification in the model by not rejecting the corresponding null hypotheses. However, the coefficient of the lagged dependent variable is not in the interval for the good estimates of the true parameter as found before.

A problem with the original Arellano-Bond estimator is that lagged levels are poor instruments for first differences if the variables are close to a random walk (Roodman, 2008). Blundell and Bond (1998) following Arellano and Bover (1995) suggest a "system" GMM estimation which they report as "more efficient and stable than the Arellano-Bond procedure" (Alberini and Filippini, 2010: 14). The original equation in levels is added to the equation in difference form and with this system of equations, additional instruments can be brought to bear to increase efficiency. In the level equation, variables in levels are instrumented with suitable lags of their own first differences. The assumption needed is that these differences are uncorrelated with the unobserved country effects (Roodman, 2008). Infact this assumption follows from the assumption that the correlation between the level variables and the fixed effects is constant over time.

We use one instrument for each variable and lag distance. In the model estimation presented in Table 8.16, the autocorrelation test indicates the absence of second order autocorrelation which is necessary for the validity of the model and Hansen tests result shows that the overidentifying restrictions are valid. Therefore, the results show that there is no misspecification in the model. However, the coefficients except the one for lagged dependent variable are not significant and also sign of coefficient on oil price volatility variable is contrary to expectations.

Mileva (2007) states that some studies add only the variables that are not correlated with the fixed effects into the levels equation. As we suspect that real electricity price, urbanization ratio and per capita real GDP variables might be correlated with the fixed effects, we exclude these variables and also the lags of differenced per capita electricity consumption from the levels equation. We obtain similar results as in two-step difference GMM. Results from BB2 estimation shows that electricity consumption is inelastic with respect to price and income with (0.09428, -0.07626) income and price elasticities.

8.7. Estimation of Panel Cointegration Relation

In section 8.3, we have found cointegrating relation among the variables. In this section, we use various methods to estimate this long run relationship. In order to estimate the long run relation between panel variables, different estimators have been proposed by researchers and we apply estimators such as pooled OLS estimator; panel group fully modified OLS (FMOLS) estimator of Pedroni (1996,2000) and Phillips and Moon (1999); panel dynamic OLS (PDOLS) estimator of Mark and Sul (2003); mean group (MG) estimator of Pesaran et al. (1999) and Pesaran and Smith (1995); panel two-step estimator of Breitung (2005); continuous-updated fully modified (CUP-FM) estimator of Bai and Kao (2006); and Common Correlated effects mean group (CCE-MG) and pooled (CCEP) estimators of Pesaran (2006) and compare the estimation results. Some of the previous findings of researchers for the comparison between these methods can be summarized as follows; Kao and Chiang (2000) shows that panel DOLS has better performance than panel OLS and panel FMOLS. Superiority of panel group FMOLS over panel within dimension FMOLS with respect to asymptotic properties has been demonstrated by Pedroni (2000). Based on Monte Carlo experiments, Bai and Kao (2006) emphasize on the better small sample properties of CUP-FM estimator compared to two-step FM and OLS estimators.

We ignore the short run dynamics and given the variables are cointegrated, the static long-run relation to be estimated can be expressed as follows;

$$lnpcec_{it} = \alpha + \beta * lnpcgdp_{it} + \gamma * lnrep_{it} + \theta * uratio_{it} + u_{it} \qquad (8.8)$$

By applying OLS to the above panel cointegrating regression, we obtain inconsistent estimator of the cointegrating vector as indicated by Baltagi (2008). On the other hand, in the time series data analysis, although, OLS estimation yields super consistent estimator, “OLS estimator for the cointegrating parameter has non-normal distribution, inferences based on t statistic can be misleading” (Verbeek, 2004: 317).

In the equation, error term captures the electricity consumption dynamics and adjustments to the long run equilibrium.

According to Table 8.14, estimation results regarding to sign, size and statistical significance of long-run coefficients vary significantly based on the method employed, deterministic term specification and accounting for the heterogeneity and cross-sectional dependence among the countries. A priori, we expect positive impact of income and urbanization ratio, whereas, negative effect of electricity price on the electricity consumption. Our expectations on the sign of coefficients are supported by estimators such as POLS, FMOLS, PDOLS with constant and heterogeneous linear trend, PDOLS with constant, heterogeneous linear trend and common time effects, MG with intercept, two step estimators with individual specific intercept and individual specific trend, CUP-FM, CCE-MG and CCEP with intercept, and CCEP with intercept and linear time trend.

Among these estimations, for all the variables we obtain statistically significant coefficients at most 10% significance level for POLS estimation, FMOLS estimation, and two step estimations with individual specific intercept and individual specific trend. Therefore, we can conclude that long-run relation between electricity consumption and the explanatory variables are significant. The estimated coefficients on income and electricity price give us long-run income and price elasticities of electricity consumption. From estimation results, we observe that long run income and price elasticities are low (less than one in absolute size) indicating that long run electricity consumption is inelastic with respect to income and own-price. Any energy policies based on income or electricity price will not be successful to affect long run electricity consumption.

Table 8.14 Alternative Methods for the Estimation of Panel Cointegration Relation for OECD countries

lnpcec (dep. var.)	lnpcgdp	lnrep	uratio
Methods			
1. POLS	1.30 (32.55) ***	-0.59 (-8.33) ***	0.32 (2.08)**
2. FMOLS	0.53 (20.86) ***	-0.02 (-4.72) ***	3.12 (13.98) ***
3. PDOLS[1]	0.57 (6.23) ***	0.26 (1.45)	2.66 (3.44) ***
4. PDOLS[2]	0.59 (6.26) ***	0.23 (1.20)	2.60 (3.34) ***
5. PDOLS[3]	0.39 (6.61) ***	0.10 (2.00)**	2.30 (2.91) ***
6. PDOLS[4]	0.36 (5.81) ***	0.13 (2.54)**	2.27 (2.98) ***
7. PDOLS[5]	0.08 (1.61)	-0.11 (-4.28) ***	1.35 (2.58) ***
8. PDOLS[6]	0.07 (1.34)	-0.09 (-3.67) ***	1.40 (2.76) ***
9. MG[7]	0.58 (5.69) ***	-0.06 (-1.27)	1.74 (0.71)
10. MG[8]	0.27 (3.96) ***	-0.06 (-1.53)	-2.70 (-1.07)
11. Two step[9]	0.48 (16.75) ***	-0.26 (-12.48) ***	2.48 (11.24) ***
12. Two step[10]	0.30 (10.30) ***	-0.06 (-4.43) ***	1.32 (6.21) ***
13. CUP-FM[11]	2.74 (0.44)	-0.16 (-0.05)	13.62 (0.29)
14. CUP-FM[12]	3.08 (0.07)	-0.01 (-0.001)	15.35 (0.05)
15. CCE-MG[13]	0.35 (2.97) ***	-0.04 (-1.05)	3.01 (1.05)
16. CCEP[13]	0.32 (2.76) ***	-0.003(-0.10)	0.19 (0.14)
17. CCE-MG[14]	0.38 (3.00) ***	-0.04 (-1.28)	-0.60 (-0.09)
18. CCEP[14]	0.39 (3.04) ***	-0.02 (-0.98)	2.01 (0.96)

Note: Asymtotic distributions of t tests for panel FMOLS Group Mean, PDOLS, MG, PMG, two step , CUP-FM, CCE-MG and CCEP estimators are standard normal. Test's null and alternative hypothesis are $H_o:\beta_i = 0$ and $H_a:\beta_i \neq 0$ for all i. Test values are provided in parentheses. Common intercept is included in POLS. Inference is based on t-distribution. In PDOLS model, lags and leads are taken as one as suggested. And t-statistics is computed using standard error based on Andrews and Monahan's Pre-whitening method to deal with autocorrelation problem. In FM estimators to obtain long run covariance matrix, Barlett kernel window width is set according to $(4*(T/100)^{2/9})$.
[1]Model without constant, [2]Model without constant + common time effect, [3]Model with constant(Fixed effect), [4]Model with constant(Fixed effect) + common time effect, [5]Model with constant and heterogeneous linear trend, [6]Model with constant and heterogeneous linear trend + common time effect, [7]We include intercept only, [8]Intercept and linear time trend are included, [9]Model with individual specific intercept. One lagged difference is included, [10]Model with individual specific trend. One lagged difference is included, [11]CUP-FM accounts for cross-sectional dependence. Two stage estimation, [12]Iterative estimation. In CUP-FM, maximum number of factors is taken as 1, [13]Standard errors based on non-parametric variance estimator in Pesaran (2006) is employed to calculate t-ratios. Intercept is included. [14]Standard errors based on non-parametric variance estimator in Pesaran (2006) is employed to calculate t-ratios. Intercept and linear time trend are included. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%.

8.8. Estimation of Panel Error Correction Model

According to the Granger representation theorem, "if a set of variables are cointegrated, then there exists a valid error-correction representation of the data" (Verbeek, 2004: 318). In order to investigate the short run and long run impacts of income, electricity price, urbanization ratio and oil price volatility on electricity consumption, following Pesaran et al. (1999), we will estimate a panel error correction model given by the reparametrization of the following panel ARDL$(p_i, q_i, k_i, l_i, m_i)$ model;

$$lnpcec_{it} = \alpha_i + \sum_{j=1}^{p_i} \beta_{ij}\, lnpcec_{it-j} + \sum_{j=0}^{q_i} \delta_{ij}\, lnpcgdp_{it-j} + \sum_{j=0}^{k_i} \theta_{ij}\, lnrep_{it-j} + \sum_{j=0}^{l_i} \gamma_{ij}\, uratio_{it-j} + \sum_{j=0}^{m_i} \lambda_j\, h4\_poil_{t-j} + \varepsilon_{it} \quad (8.9)$$

When we reparametrize the above equation, we obtain ECM expression as follows;

$$\Delta lnpcec_{it} = \varphi_i(lnpcec_{it-1} - \alpha_i^* - \delta_i^* lnpcgdp_{it} - \theta_i^* lnrep_{it} - \gamma_i^* uratio_{it} - \lambda^* h4\_poil_t) + \sum_{j=1}^{p_i-1} \beta_{ij}{}^{**}\, \Delta lnpcec_{it-j} + \sum_{j=0}^{q_i-1} \delta_{ij}{}^{**}\, \Delta lnpcgdp_{it-j} + \sum_{j=0}^{k_i-1} \theta_{ij}{}^{**} \Delta\, lnrep_{it-j} + \sum_{j=0}^{l_i-1} \gamma_{ij}{}^{**}\, \Delta uratio_{it-j} + \sum_{j=0}^{m_i-1} \lambda_j{}^{**}\, \Delta h4\_poil_{t-j} + \varepsilon_{it} \quad (8.10)$$

where,

$\varphi_i = -\left(1 - \sum_{j=1}^{p_i} \beta_{ij}\right)$; $\alpha_i^* = -\alpha_i/\varphi_i$; $\delta_i^* = -\sum_{j=0}^{q_i} \delta_{ij}/\varphi_i$; $\theta_i^* = -\sum_{j=0}^{k_i} \theta_{ij}/\varphi_i$; $\gamma_i^* = -\sum_{j=0}^{l_i} \gamma_{ij}/\varphi_i$; $\lambda^* = -\sum_{j=0}^{m_i} \lambda_j/\varphi_i$; i = 1,2,...,27, t = 1, 2,....,23. ε_{it} is independently distributed error term across i and t. φ_i is the coefficient on error correction term and it is expected to be negative. It determines the speed of adjustment to the equilibrium. $\beta_{ij}{}^{**}, \delta_{ij}{}^{**}, \theta_{ij}{}^{**}, \gamma_{ij}{}^{**}, and\ \lambda_j{}^{**}$ are short run coefficients, whereas, $\delta_i^*, \theta_i^*, \gamma_i^*, and\ \lambda^*$ are long run coefficients. α_i is the fixed effects.

To estimate the ECM, we employ mean group (MGE) and pooled MGE (PMGE) estimators proposed by Pesaran et al. (1999). Pesaran and Smith (1995) have shown that from MGE, consistent estimates for the average of parameters are obtained without imposing restrictions on the coefficients and errors variances across cross-sections. On the other hand, PMGE restricts each cross-section to have same long-run coefficients but does not put any constraint on intercepts, short run coefficients and error variances across cross-sections. It may be reasonable to assume same long-run relation between variables across countries due to rapid globalization and also for the consumption, due to "common life cycle behaviour in the long run, while in the shorter term, institutions, differences in consumer preference and financial structure may play a role (such as scope of credit availability), leading to differing dynamics" (Barrell and Davis, 2004: 6). To test homogeneity of long-run coefficients, we calculate likelihood ratio (LR) statistics as 921.8756 with associated p-value 0.0000. In this case, we strongly reject the homogeneity of long-run coefficients. However, Pesaran et. al. (1999) argue that LR test usually rejects equality of long-run coefficients, short-run coefficients or errors variances in cross-country studies and suggests to use Hausman type test as an alternative. Both joint and variable by variable Hausman tests cannot reject null of no difference between PMG and MG estimators.

As, PMG estimator is efficient and consistent under the null hypothesis, we can assume homogeneity of long-run coefficients. Our inferences and interpretations will be based on the results obtained from Pooled MG estimation. Table 8.15 shows the estimation results and in Table 8.16, we present the diagnostic tests for ECMs estimated for each country, separately.

Findings from diagnostic tests for each of country-specific EC equation estimation based on PMG estimator can be summarized as follows; In 13 country-specific equations, there is no any problem of serial correlation and Ramsey's Reset tests for equations of 16 countries does not indicate any functional form misspecification at

5% significance level. There exists problems of nonnormal errors and heteroscedasticity in 2 and 5 country-specific EC equations, respectively.

When we compare the MG and PMG estimation results, we can observe that speed of adjustment is higher for MG estimate. This is not surprising, as stated by Pesaran et al. (1999), homogeneity restriction leads to upward bias in the coefficient of lagged dependent variable. And also, t ratios associated with PMG estimates are higher than the ones for MG estimates in absolute size.

In PMG estimation, signs of long run coefficients are all in line with the a priori expectations and statistically significant long run coefficients are obtained for lnpcgdp, lnrep and uratio variables. As in the estimation of static long-run equation, long-run electricity consumption is inelastic with respect to income and electricity price. Error correction term is negative and significant. This is an indication of adjustment of electricity consumption towards equilibrium and also existence of cointegration between variables. Although in the long-run, oil price volatility does not have a significant impact on electricity consumption, contemporaneous negative and significant effect is observed in the short-run at 5% significance level. In the short run, besides oil price volatility, only lagged first difference of income has a significant influence on contemporaneous change of electricity consumption at 10% significance level.

Short run income and price elasticities are found to be 0.070 and 0.050, respectively, however, both of them are statistically insignificant. Positive short run price elasticity can be a sign for high subsidies provided in some countries as also indicated by Bhargava et al. (2009) for agriculture sector of India.

Table 8.15 PMG and MG Estimates of Panel Error Correction Model

Dependent variable: lnpcec	Pooled MGE Estimates	MGE Estimates	h-test [p-value][1]
Long-run Coefficients			
lnpcgdp	0.324 (18.174)***	0.459 (3.711)***	1.21 [0.27]
lnrep	-0.116 (-8.772)***	-0.123 (-1.626)	0.01 [0.93]
uratio	4.831 (48.966)***	3.567 (1.490)	0.28 [0.60]
h4_poil	-0.018 (-0.041)	2.422 (1.403)	2.14 [0.14]
Joint Hausman test			5.93 [0.20]
Error Correction Coefficients			
φ	-0.559 (-3.957)***	-1.115 (-6.277)***	
Short-run Coefficients			
Δlnpcec$_{t-1}$	0.006 (0.071)	0.167 (1.511)	
Δ lnpcgdp$_t$	0.070 (0.594)	0.008 (0.059)	
Δlnpcgdp$_{t-1}$	-0.114 (-1.804)*	-0.149 (-0.977)	
Δ lnrep$_t$	0.050 (1.563)	0.024 (0.379)	
Δ lnrep$_{t-1}$	-0.040 (-1.209)	-0.024 (-0.555)	
Δ uratio$_t$	7.493 (1.529)	8.336 (1.447)	
Δuratio$_{t-1}$	4.928 (0.836)	-0.539 (-0.137)	
Δh4_poil$_t$	-1.018 (-2.199)**	-0.701 (-1.138)	
Δ h4_poil$_{t-1}$	-0.187 (-0.954)	-0.420 (-0.998)	
constant	1.456 (3.749)***	0.531 (0.200)	

Note: Asymtotic distributions of t ratio are standard normal. Test's null and alternative hypothesis are H_o:$\beta_i = 0$ and H_a:$\beta_i \neq 0$ for all i. Test values are provided in parentheses. Maximum number of lags for each variable is determined as 2. Selection of the lag orders for each group is based on AIC. We use mean group estimates as initial estimates of the long-run parameters for the pooled maximum likelihood estimation. To obtain PMGE estimates, maximum likelihood approach with Back-Substitution algorithm is employed following Pesaran et al. (1999). We add only constant. Estimation is repeated by adding linear time trend; however, we obtain the estimated coefficients such that their signs are contrary to theoretical expectations. Therefore, to save space, results are not shown here. We use raw data as the model includes cross-section invariant variable assuming cross-sectional independence of panel series.

*, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%.

[1] h-test is the Hausman test statistic with its associated p-value in squared bracket. h-test statistics is asymptotically distributed as $\chi^2(4)$ under null hypothesis.

Table 8.16 Diagnostic Tests Results

A. PMGE						
Countries	**CH-SC**	**CH-FF**	**CH-NO**	**CH-HE**	**RBARSQ**	**LL**
Australia	8.69***	11.3***	1.23	0.53	-0.51	66.05
Austria	147.01***	37.66***	1.61	6.11***	-3.74	32.92
Belgium	8.9***	0.5	0.22	0.27	0.22	61.69
Canada	0.39	3.81*	5.09*	1.24	0	63.06
Denmark	1.9	23.35***	0.05	3.12*	0.71	51.98
Finland	0.93	0	0.74	0.97	-0.05	50.73
France	0.19	0.08	1.36	0.01	-0.09	58.57
Germany	0.87	0.65	3.59	2.54	0.1	66.94
Greece	6.3**	17.77***	0.7	0.49	-0.2	62.56
Hungary	12.35***	0.02	1.07	0.08	0.36	48.86
Ireland	3.6*	5.53**	1.45	2.08	0.42	63.94
Italy	48.34***	33.9***	0.19	7.76***	-11.45	37.25
Japan	146.77***	34.12***	0.92	0.08	-0.7	52.01
Korea, Rep.	7.64***	2.01	8.33**	4.08**	0.66	55.77
Luxembourg	56.24***	11.2***	0.44	0	-0.26	45.02
Mexico	0.05	1.6	0.34	1.79	-0.34	49.83
Netherlands	24.67***	0.33	29.76***	0	-0.31	41.87
New Zealand	45.87***	0.18	0.61	1.71	-0.14	54.26
Norway	215.94***	0.24	1.78	13.72***	-21.21	15.4
Portugal	0.25	5.74**	1.1	1.34	0.6	62.31
Slovak Rep.	0.93	0.36	5.2*	0.18	0.31	39.49
Spain	9.33***	0.21	1.27	8.54***	-0.01	54.01
Sweden	2.03	3.63*	0.26	0.05	-0.2	46.73
Switzerland	0.29	0.21	1.56	0.48	-0.15	40.84
Turkey	0.15	13.32***	0.04	1.53	-0.3	48.37
U.K.	68.74***	0.51	0.36	0.05	-0.37	57.88
U.S.	4.22*	45.93***	1.71	0.17	0.38	67.25
B. MGE						
Countries	**CH-SC**	**CH-FF**	**CH-NO**	**CH-HE**	**RBARSQ**	**LL**
Australia	0.45	2.49	0.83	3.51*	0.73	83.96
Austria	10.06***	0.35	2.77	0.3	0.8	66.05
Belgium	4.19**	7.81***	0.54	0	0.79	75.61
Canada	8.41***	10.12***	0.06	0.44	0.67	74.83
Denmark	1.33	4.15**	8.36**	0.21	0.89	62.07
Finland	1.8	0.53	0.07	0.28	0.58	60.22

Table 8.16 (Continued)

Countries	Ch-SC	CH-FF	CH-NO	CH-HE	RBARSQ	LL
France	0.06	1.35	0.86	0.91	0.42	65.45
Germany	6.65***	1.43	1.87	0.02	0.45	72.08
Greece	8.2***	4.05**	0.32	1.24	0.83	83.29
Hungary	1.93	0.04	0.13	1.48	0.73	57.75
Ireland	8.3***	4.55**	0.58	0.27	0.88	80.48
Italy	1.53	7.67***	0.33	0.19	0.9	87.99
Japan	0.37	4.62**	1.13	0.11	0.85	78.41
Korea, Rep.	5.17**	3.68*	1.14	1.85	0.9	68.42
Luxembourg	5.25**	3.17*	1.41	1.01	0.9	71.31
Mexico	0.05	2.79*	1.38	0	0.55	61.3
Netherlands	2.18	0.71	51.47***	1.16	0.48	52.06
New Zealand	1.19	0.92	1.21	4.48**	0.56	64.29
Norway	1.17	0.02	2	0.5	0.73	61.7
Portugal	5.83**	4.6**	0.26	0.56	0.79	69.28
Slovak Rep.	3.62*	0.1	1.48	0	0.58	44.7
Spain	9.17***	12.3***	0.08	3.66*	0.79	70.71
Sweden	3.13*	0.01	7.54**	0.06	0.85	68.72
Switzerland	3.12*	0.57	0.79	0.92	0.74	56.56
Turkey	1.75	0.16	0.76	0.07	0.68	63.22
U.K.	3.06*	1.95	2.2	0.55	0.7	74.43
U.S.	2.06	0.96	1.67	1.71	0.84	81.63

Notes: CH-SC: Godfrey's test of residual serial correlation, CH-FF: Ramsey's RESET test of functional form, CH-NO: Jarque-Bera's test of the normality, CH-HE: Test of Heterosckedasticity. CH-SC, CH-FF and CH-HE statistics are asymptotically distributed as $\chi^2(1)$ under null hypothesis of no serial correlation in residuals, no misspecification in functional form, and no heteroscedasticity in residuals, respectively. CH-NO statistics is asymptotically distributed as $\chi^2(2)$ under null hypothesis of normality. RBARSQ: Adjusted R squared. LL: Maximized log-likelihood. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%.

In order to avoid cross-sectional dependency problem, we estimate ECM with Common Correlated effects mean group (CCE-MG) and pooled (CCEP) estimators of Pesaran (2006) and compare the estimation results with MG and PMG estimates. Following the residual-based testing procedure and Holly, Pesaran and Yamagata (2006), first we estimate the cointegration relation in equation (8.11) using pooled CCE estimator and apply CIPS test to the residuals ($\hat{u}_{it}$) of this estimation. If we reject null of unit root in the residuals of cointegration equation, then we can say that the variables are cointegrated and we can proceed by estimating a panel error correction model given in equation (8.12) by CCE-MG and CCEP estimators.

$$lnpcec_{it} = \alpha_i + \beta_i lnpcgdp_{it} + \gamma_i lnrep_{it} + \theta_i uratio_{it} + u_{it} \tag{8.11}$$

where $u_{it} = \sum_{\ell=1}^{m_1} \xi_{1i\ell} f_{1\ell t} + \vartheta_{1it}$ such that we allow for multifactor error structure.

$$\begin{aligned}\Delta lnpcec_{it} = \varphi_i\big(&lnpcec_{it-1} - \hat{\alpha}_i - \hat{\beta} lnpcgdp_{it-1} - \hat{\gamma} lnrep_{it-1} - \hat{\theta} uratio_{it-1}\big)\\ &+ \beta_{i1}{}^{**}\Delta lnpcec_{it-1} + \delta_{i0}{}^{**}\Delta lnpcgdp_{it} + \delta_{i1}{}^{**}\Delta lnpcgdp_{it-1}\\ &+ \theta_{i0}{}^{**}\Delta lnrep_{it} + \theta_{i1}{}^{**}\Delta lnrep_{it-1}\\ &+ \gamma_{i0}{}^{**}\Delta uratio_{it} + \gamma_{i1}{}^{**}\Delta uratio_{it-1} + \lambda_0{}^{**}\Delta h4\_poil_t\\ &+ \lambda_1{}^{**}\Delta h4\_poil_{t-1} + \varepsilon_{it}\end{aligned} \tag{8.12}$$

where, $\varepsilon_{it} = \sum_{\ell=1}^{m_2} \xi_{2i\ell} f_{2\ell t} + \vartheta_{2it}$.

We have already presented the CCE estimation results of cointegration relation in Table 8.14 of section 8.7. Table 8.17 and 8.18 show the results of CD test and CIPS test for the residuals obtained from CCEP estimation of long-run relation, respectively.

Table 8.17 Pesaran (2004) CD test of Residuals from CCEP estimation of Cointegration Relation

	CD-test	p-value	Corr	abs(corr)
$\hat{u}_{it}$	29.04***	0.000	0.323	0.605

Note: *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%.

Table 8.18 Pesaran (2006) CADF Tests Results for Residuals of CCEP estimation of Cointegration Relation

	Intercept	**Intercept and Trend**
CIPS Statistics	-2.1235*	-2.2535

Note: The lag lengths (p) are selected according to Schwarz information criterion. Maximum lag is taken as 2. The critical values for the CIPS test were obtained from Pesaran (2006), in Table 2b for the test equation with intercept only as -2.30, -2.15 and -2.07;and in Table 2c for the test equation with intercept and trend as -2.81, -2.66 and -2.58 at 1%, 5% and 10% levels of significance, respectively., *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%. Same results are obtained when extreme t-values are truncated.

CD test indicates that there exists cross-sectional dependence problem in the residuals. Therefore, we have shown necessity of using Pesaran (2006) CADF Tests to detect stationarity properties of residuals. Although CIPS statistics indicate the presence of unit root at most 10% level for the test equation with only intercept and at conventional levels for the one with trend and intercept, and therefore there is no any cointegration among the variables based on approach proposed by Holly, Pesaran and Yamagata (2006), we estimate ECM by CCE-MG and CCEP estimators depending on the conclusions drawn from other more sophisticated cointegration tests assuming that the long-run relation is homogenous across countries.

CD test for the residuals from OLS-MG estimation show that there is no cross-sectional dependence in the residuals. Based on CCEP estimation of long run relation, only income has a significant impact on electricity consumption. When we compare error correction coefficients among OLS-MG, CCEP and CCE-MG estimates, sign of OLS-MG estimate is contrary to our expectations implying divergence from long-run equilibrium path. Results based on CCEP and CCE-MG estimations are close to each other. 23% and 62% proportion of deviation from the equilibrium path is corrected in each year according to CCEP and CCE-MG estimations, respectively. In the short run, contemporaneous positive and significant effect of income change; and negative and significant impact of lagged first difference of electricity consumption on contemporaneous change of electricity consumption are observed at most 10% significance level. In addition to these, OLS-MG estimation results show that contemporaneous change of electricity price and lagged oil price volatility change have significant negative and positive influences in the short run, respectively at 5% level of significance.

Table 8.19 OLS-MG, CCEP and CCE-MG Estimates of Panel Error Correction Model

Dependent variable: lnpcec	**OLS- MG Estimates**	**CCEP Estimates**	**CCE-MG Estimates**
Long-run Coefficients			
lnpcgdp	0.32 (2.76) ***	0.32 (2.76) ***	0.32 (2.76) ***
lnrep	-0.003 (-0.10)	-0.003 (-0.10)	-0.003 (-0.10)
uratio	0.19 (0.14)	0.19 (0.14)	0.19 (0.14)
Error Correction Coefficients			
φ	0.003 (2.89)***	-0.23 (-1.49)	-0.62 (-6.07)***
Short-run Coefficients			
$\Delta lnpcec_{t-1}$	-0.22 (-3.73)***	-0.29 (-2.78)***	-0.15 (-1.89)*
Δ $lnpcgdp_t$	0.29 (3.52)***	0.42 (1.83)*	0.68 (4.73)***
$\Delta lnpcgdp_{t-1}$	0.10 (1.14)	0.13 (0.63)	-0.17 (-0.97)
Δ $lnrep_t$	-0.07 (-2.26)**	-0.03 (-0.90)	-0.03 (-0.71)
Δ $lnrep_{t-1}$	-0.04 (-0.93)	-0.01 (-0.36)	0.02 (0.37)
Δ $uratio_t$	4.78 (1.53)	-0.86 (-0.11)	-13.20 (-0.71)
$\Delta uratio_{t-1}$	-6.42 (-1.43)	1.67 (0.16)	-17.57 (-1.40)
$\Delta h4\_poil_t$	-0.06 (-0.19)	-0.00 (-)	-0.09 (-)
Δ $h4\_poil_{t-1}$	0.52 (2.16)**	-0.00 (-)	-0.01 (-)
constant	0.001 (4.41)***	-0.00 (-)	0.000035 (-)
CD test	-0.29162 [0.77058]		

Note: Asymtotic distributions of t ratio are standard normal. Test's null and alternative hypothesis are H_o:$\beta_i = 0$ and H_a:$\beta_i \neq 0$ for all i. Test values and p-values are provided in parentheses and square brackets, respectively. We add only constant. Estimation is repeated by adding linear time trend to the model, similar results are obtained with one exception that the error correction term in CCEP estimation becomes statistically significant. To save space, we do not present the results, however, results can be available upon request. Standard errors based on non-parametric variance estimator in Pesaran (2006) are employed to calculate t-ratios of OLS-MG, CCEP, and CCE-MG estimates. *, **, *** shows the statistical significance of test statistics at 10%, 5% and 1%.

According to the estimation results based on CCE-MG estimation, long run elasticities are smaller than short run's. Amarawickrama and Hunt (2008) have explained this finding as a result of inflexible energy-using capital stock and appliance stock owned by households and firms or due to wrong modeling of energy efficiency impact.

8.9. Panel Granger Causality Test

In order to propose suitable policy recommendations about the electricity demand management, we need to test if there is a causal relation between electricity consumption and income by employing panel Granger causality test. We employ a test based on Vector Error Correction Model (VECM). First of all, we test for the existence of cointegration between the two variables by Pedroni (1999, 2004) and Kao (1999) residual-based cointegration tests, Combined Individual panel cointegration test (Fisher/Johansen), Westerlund (2006) panel LM cointegration test and Westerlund (2007) error correction-based cointegration test.

Tables 8.20, 8.21, and 8.22 show the results. We obtain conflicting results by different tests under different assumptions on the cross-sectional independency, poolability, and different deterministic term specifications. However, majority of them indicate the presence of cointegration among lnpcec and lnpcgdp. Therefore, we continue our analysis assuming that lnpcec and lnpcgdp are cointegrated.

As we establish the existence of cointegration among the variables, we can employ the panel Granger causality test based on VECM. Following Ağır et al. (2011), we consider the bivariate panel VECM in equation (8.13) allowing for different coefficients in the cointegration relation across countries, however, assuming homogeneous error correction coefficient and short run dynamics, and cross-sectional independence.

$$\Delta lnpcec_{it} = \delta_{10} + \varphi_1\left(lnpcec_{it-1} - \hat{\alpha}_i - \hat{\beta}_i lnpcgdp_{it-1}\right)$$
$$+ \sum_{j=1}^{k} \delta_{11j} \Delta lnpcec_{it-j} + \sum_{j=1}^{k} \delta_{12j} \Delta lnpcgdp_{it-j} + \varepsilon_{1it}$$

$$\Delta lnpcgdp_{it} = \delta_{20} + \varphi_2\left(lnpcec_{it-1} - \hat{\alpha}_i - \hat{\beta}_i lnpcgdp_{it-1}\right)$$
$$+ \sum_{j=1}^{k} \delta_{21j} \Delta lnpcec_{it-j} + \sum_{j=1}^{k} \delta_{22j} \Delta lnpcgdp_{it-j} + \varepsilon_{2it} \qquad (8.13)$$

where, k is the lag length selected by AIC, $\hat{\alpha}_i$ and $\hat{\beta}_i$ are obtained from the FMOLS estimation of the cointegrating relation between electricity consumption and GDP for each country.

In order to test the causality from GDP (electricity consumption) to electricity consumption (GDP), we test the following joint null hypothesis by Wald statistics, H_0: $\delta_{121} = \delta_{122} = \cdots = \delta_{12k} = 0$ (H_0: $\delta_{211} = \delta_{212} = \cdots = \delta_{21k} = 0$). Results are shown in Table 8.23. The test results indicate the bidirectional causality between electricity consumption and GDP.

Öztürk (2010) and Payne (2010) provided literature survey on electricity consumption-growth nexus. In the literature, studies have tested four hypothesis: growth hypothesis, conservation hypothesis, feedback hypothesis, and neutrality hypothesis. The neutrality hypothesis postulates the absence of any causal relation between electricity consumption and GDP implying that "electricity conservation policies will have no effect on economic growth" (Payne, 2010: 723). In the feedback hypothesis, bidirectional causality between electricity consumption and GDP is expected. "Under the feedback hypothesis, an energy policy oriented toward improvements in electricity consumption efficiency may not adversely affect economic growth" (Payne, 2010: 723). "Policy makers should take into account the feedback effect of real GDP on energy consumption by implementing regulations to reduce energy use" (Dobnik, 2011: 4).

Table 8.20 Pedroni (1999, 2004) and Kao (1999) Residual-based Cointegration Test

A. Pedroni (1999, 2004) Residual-based Cointegration Test[1]			
	No deterministic component	**Only intercept**	**Intercept+ trend**
Panel Tests			
v-Statistic	-2.25484** (0.03140)	1.42537 (0.14450)	4.74125*** (0.00000)
ρ-Statistic	1.10633 (0.21630)	-3.32541*** (0.00160)	-1.92890* (0.06210)
t-Statistic (PP - non-parametric)	0.13165 (0.39550)	-4.99290*** (0.00000)	-6.44067*** (0.00000)
t-Statistic (ADF - parametric)	1.19507 (0.19530)	-5.05944*** (0.00000)	-7.72600*** (0.00000)
Group Mean Tests			
ρ-Statistic	3.00466*** (0.00440)	-1.53029 (0.12370)	0.79107 (0.29180)
t-Statistic (PP - non-parametric)	0.29753 (0.38170)	-5.02684*** (0.00000)	-4.68439*** (0.00000)
t-Statistic (ADF - parametric)	0.24282 (0.38740)	-4.92505*** (0.00000)	-5.28490*** (0.00000)

B. Kao (1999) Residual-based Cointegration Test[2]	
t-Statistic (ADF)	0.627794 (0.26510)

Note: The null hypothesis is that there is no cointegration. Under alternative hypothesis of Pedroni tests; common AR coefficient is assumed for all countries in panel tests; however, group mean tests allow for heterogeneity across countries. P-values are provided in parentheses. The lag lengths (p) are selected according to Schwarz information criterion. Maximum lag length for cross-section *i* is computed as $[\min (12, \frac{T_i}{3})(\frac{T_i}{100})^{0.25}]$, where T_i shows the time dimension of the cross-section *i*. For Newey-West bandwidth selection, Bartlett kernel was used.

[1]The first stage estimation results employing mean group estimator are given as below;

$$\widehat{lnpcec}_{it} = 0.869327 * lnpcgdp_{it}$$
$$\widehat{lnpcec}_{it} = -0.05386 + 0.887320 * lnpcgdp_{it}$$
$$\widehat{lnpcec}_{it} = 5.473172 + 0.013023 * t + 0.313504 * lnpcgdp_{it}$$

[2]Kao (1999) assumes that first stage regression includes cross-section specific intercepts and imposes homogeneous coefficients on the regressors in the first stage regression. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%. The first stage estimation results are given as follows;

$$\widehat{lnpcec}_{it} = -0.2389437 + 0.9189981 * lnpcgdp_{it} + \sum_{i=2}^{27} \mu_i D_{it}$$

Table 8.21 Combined Individual Panel Cointegration Test (Fisher/Johansen)

			Number of Cointegration Relation	
			None	**At most 1**
Fisher Statistics	**S1**[1]	Trace Test	165.7 (0.0000)***	85.27 (0.0043)***
		Max Eigenvalue Test	144.0 (0.0000)***	85.27 (0.0043)***
	S2[1]	Trace Test	198.5 (0.0000)***	76.56 (0.0234)**
		Max Eigenvalue Test	183.4 (0.0000)***	76.56 (0.0234)**
	S3[1]	Trace Test	158.9 (0.0000)***	69.09 (0.0811)*
		Max Eigenvalue Test	156.5 (0.0000)***	69.09 (0.0811)*
	S4[1]	Trace Test	190.5 (0.0000)***	81.52 (0.0091)***
		Max Eigenvalue Test	161.8 (0.0000)***	81.52 (0.0091)***
	S5[1]	Trace Test	236.0 (0.0000)***	176.2 (0.0000)***
		Max Eigenvalue Test	171.8 (0.0000)***	176.2 (0.0000)***

[1]Deterministic trend specifications are as follows; S1: No intercept or trend in cointegration equation (CE) or VAR (No trend in data); S2:Intercept in CE but no intercept in VAR (No trend in data); S3: Intercept in CE and VAR (Linear trend in data); S4: Intercept and trend in CE and no trend in VAR (Linear trend in data); S5: Intercept and trend in CE and linear trend in VAR (Quadratic trend in data). Lag number is taken as 2 for all countries because of small time dimension (T=23). Similar results are obtained using 1 lag except for maximum eigenvalue and trace tests in the specification 4, such that, tests show the evidence of one cointegrating relation at 1% significance level. P-values provided in parentheses are computed using asymptotic χ^2 distribution. *, **, *** show the statistical significance of test statistic at 10%, 5%, and 1%.

The growth hypothesis assumes uni-directional causality from electricity consumption to GDP, therefore any energy conservation policy can harm economic growth, whereas, the evidence of uni-directional causality running from electricity consumption to GDP asserted by the conservation hypothesis implies that energy conservation will have no or little effect on economic growth.

According to Payne (2010), among the countries analyzed by the studies surveyed, for the 31.15%, 27.87%, 22.95%, 18.03% of the coutries, studies have found results in line with the neutrality hypothesis, the conservation hypothesis, the growth hypothesis, and the feedback hypothesis, respectively.

Table 8.22 Westerlund (2006) Residual-based Panel LM and Westerlund (2007) Error Correction-based Cointegration Tests

A. Westerlund (2006) Residual-based panel LM Cointegration Test[1]		
	Only intercept	**Intercept+ trend**
LM Statistic Value	2.006 (0.022) [a]** (0.860) [b]	6.359 (0.000) [a]*** (0.000) [b]***

B. Westerlund (2007) Error Correction-based Cointegration Test[2]				
		No deterministic component[3]	**Only intercept**	**Intercept+trend**
G_τ	Value Z-Value	-1.264 -1.435 (0.076)[a]* (0.126)[b]	-2.494 -4.144 (0.000)[a]*** (0.074)[b]*	-2.996 -4.026 (0.000)[a]*** (0.600)[b]
G_α	Value Z-Value	-4.651 -0.970 (0.166)[a] (0.020)[b]**	-8.948 -1.723 (0.042)[a]** (0.030)[b]**	-7.619 3.357 (1.000)[a] (0.946)[b]
P_τ	Value Z-Value	-4.426 -1.520 (0.064)[a]* (0.132)[b]	-10.316 -2.810 (0.003)[a]*** (0.096)[b]*	-15.277 -4.917 (0.000)[a]*** (0.070)[b]*
P_α	Value Z-Value	-1.613 -1.054 (0.146)[a] (0.146)[b]	-8.025 -4.441 (0.000)[a]*** (0.014)[b]**	-10.914 -1.680 (0.047)[a]** (0.078)[b]*

Note: Barlett kernel window width is set according to $(4*(T/100)^{2/9})$. P-values are provided in parentheses. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%.

[a]The p-value is based on the asymptotic normal distribution.

[b]The p-value is based on the bootstrapped distribution.The number of replications is 500 in bootstraps.

[1]The null hypothesis is that there is cointegration. Test equation is estimated by Fully modified least squares. The first stage cointegration regressions with intercept only and with intercept and trend estimated by FMOLS group mean method are given as below, respectively;

$$\widehat{lnpcec}_{it} = -0.03209 + 0.885852 * lnpcgdp_{it}$$
$$\widehat{lnpcec}_{it} = 5.485958 + 0.012625 * t + 0.312208 * lnpcgdp_{it}$$

[2] The null hypothesis is that there is no cointegration. Leads are included to overcome the problem of correlation between regressors and residuals of ECM due to the violation of strict exogeneity of regressors causing the tests to be dependent on the nuisance parameters. Numbers of lags and leads are chosen according to AIC for each country. Mean group DOLS estimation of long run relation is given by;

$$\widehat{lnpcec}_{it} = 0.8773426 * lnpcgdp_{it}$$
$$\widehat{lnpcec}_{it} = -0.0949564 + 0.8875042 * lnpcgdp_{it}$$
$$\widehat{lnpcec}_{it} = -138.8007 + 0.0763652 * t - 0.494723 * lnpcgdp_{it}$$

Table 8.23 Panel Granger Causality Test Based on VECM (Following Ağır et al. (2011))

	Causality		
Dependent Variables	$\Delta lnpcec$	$\Delta lnpcgdp$	ECT
$\Delta lnpcec$	-	10.88526** (0.0124)	-7.11448***
$\Delta lnpcgdp$	8.066968** (0.0446)	-	5.22765***

Note: Table presents the test statistics. P-values are provided in parentheses. The lag lengths (k) are selected according to Akaike information criterion as three. The test statistics for short (long) run causality are distributed as χ^2_3 (t_{506}). $ECT = lnpcec_{it-1} - \hat{\alpha}_i - \hat{\beta}_i lnpcgdp_{it-1}$, where ECT represents the error correction term. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%.

Also, Öztürk (2010) observed that the studies found mixed results regarding to the existence and direction of causality. “The variation in results may be attributed to variable selection, model specifications, time periods of the studies, and econometric approaches undertaken” (Payne, 2010: 724). Some of the electricity demand studies also performed Granger Causality tests between the variables included into the electricity demand relation, such as, Halıcıoğlu (2007), Zachariadis and Pashourtidou (2007), Dergiadis and Tsoulfidis (2008), Jamil and Ahmad (2010), Lee and Lee (2010), Bernstein and Madlener (2011), Dergiadis and Tsoulfidis (2011), Madlener et al. (2011), and Zaman et al. (2011).

Among these studies, Lee and Lee (2010) have tested the causality between aggregate electricity consumption, electricity price, and the level of economic activity (GDP) by employing panel data on 25 OECD countries over the period from 1978 to 2004 based on trivariate panel VECM. Their results suggest a bidirectional strong causality between electricity consumption and GDP, however, electricity price was found to be strongly exogeneous. Another finding show the unidirectional causality running from GDP and electricity price to electricity consumption both in the long run and the short run. Different from this study, we assume electricity prices to be exogeneous at the beginning of the analysis and exclude it from the VECM, however, our results are somewhat similar. In the future study, we can extend the model by including other explanatory variables in order to avoid some possible biases arising from the omission of relevant variables as also suggested by Öztürk (2010) and Payne (2010). In the next section, we compare our results from the electricity demand analysis with the results of previous studies.

CHAPTER 9

COMPARISON WITH OTHER STUDIES

In this section, we compare our results with the findings of previous studies. Literature reviewed for aggregate electricity demand analysis showed that the short run and long run income (price) elasticity of electricity demand lie between 0.02 and 2.24 (-0.03 and -1.67) and 0.203 and 5.39 (-0.003 and -6.849), respectively from dynamic models, whereas studies based on static models produced the following intervals for income and price elasticities without making any distinction between the long run and the short run: (0.19 to 0.89) and (-0.09 to -0.73).

We summarize our findings for the panel data analysis of electricity demand for Turkey and OECD in Tables 9.1 and 9.2. For Turkey, by employing different volatility measures, the estimation results of the static models show that electricity demand is inelastic with respect to the income and price such that the income elasticity ranges from 0.35 to 0.49 within the range of the findings of the previous studies and price elasticity is found to be however positive between 0.04 and 0.08 contrary to the theoretical expectations. This result can be due to the omitted dynamics from the model. However, different than our study, Soysal (1985) obtained negative price elasticity from the OLS estimation of static multiple linear regression model by employing time series data over the period between 1963 and 1981. This difference can be related to the utilization of panel data in our study and consideration of province heterogeneity by province specific fixed effects, besides, the addition of variables can be another reason for the difference, such as urbanization ratio, volatility, cooling and heating degree days. In addition, she found that electricity demand is highly income elastic, but price inelastic. Moreover, our finding of significant and positive effects of urbanization ratio is in line with the result of Diabi (1998). Also, degree days are found to be significant determinants of electricity demand with boosting impact in most of the estimations. Same results are reported by Hsiao et al. (1989), Nasr et al. (2000), Abosedra et al. (2009), and Fan and Hyndman (2011) regarding to the significant and positive influence of degree days.

Significance of volatility variable varies according to the measurement. Findings show that exchange rate volatility and industrial production volatility have significant influence, however in varying directions. If the exchange rate volatility is measured by conditional variance of growth of real effective exchange rate calculated using CPI, then negative effect is obtained in line with the theories of investment under uncertainty and real options approach, however, by the use of the other measures, we find positive impacts which can be explained by the argument of precautionary savings motive and Black's (1987) claim. According to the precautionary savings motive, increased uncertainty leads increase in the investment through the reduction in consumption and the increase in savings. As investment increase stimulate the economic growth, we expect net effect of increased uncertainty on electricity consumption to be positive assuming that economic growth effect is far beyond the consumption decreasing effect. Black (1987) also claimed that the growth uncertainty raises growth. On the other hand, based on the theories of investment under uncertainty and real options effect, uncertainty causes delays in investment, production, and consumption, therefore decrease in electricity consumption is expected. Most of the empirical and theoretical studies support the adverse effect of uncertainty on economic activities and decisions, however, there are few exceptions which argue positive effects of uncertainty, as examples one can show Grier and Tullock (1989), Caporale and McKiernan (1998), Kormendi and Meguire (1985), Grier and Tullock (1989) which have found positive output growth volatility effect on the output growth; another example is Plante and Traum (2012) showed the stimulating effect of an increase in oil price volatility on investment and real GDP; and lastly, Molls (2000) demonstrated positive but insignificant effect of oil price volatility on the probability of oil production.

Table 9.1 Estimation Results of Electricity Demand Model for Turkey (Panel data on 65 provinces over the period from 1990 to 2001)

lnpcec	**A. FGLSDV coefficient estimates of Static Model**					
	h1_reexp	h2_reexc	h3_ipi	h4_poil	h5_nexcr	h6_ise100
lnpcgdp	0.499***	0.345**	0.480***	0.4527***	0.48889***	0.457***
lnrep	0.061**	0.082***	0.046*	0.0899***	0.05793*	0.084***
uratio	5.123***	5.244***	4.771***	5.1968***	5.11878***	5.158***
hdd	0.00003*	3.51E-06	9.30E-06	2.29E-05*	2.86E-05**	2.11E-05*
cdd	0.0001**	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
h1_ reexp	5.1433**					
h2_ reexc		-179.7***				
h3_ipi			63.14***			
h4_poil				0.314506		
h5_ nexcr					25.23086**	
h6_ ise100						0.3188
constant	1.217***	2.10542***	1.377***	1.5368***	1.24406***	1.516***

lnpcec	**B. Blundell and Bond (1998) System GMM Coefficient Estimates of Dynamic Model**					
	h1_reexp[1]	h2_reexc[1]	h3_ipi	h4_poil	h5_nexcr[1]	h6_ise100[1]
$lnpcec_{-1}$	0.575***	0.575***	0.548***	0.49747***	0.575***	0.575***
lnpcgdp	0.428***	0.428***	0.379***	0.34815***	0.428***	0.428***
lnrep	-0.591*	-0.591*	-0.174***	-0.1160***	-0.591*	-0.591*
uratio	1.381**	1.381**	1.5979**	3.07413***	1.381**	1.381**
hdd	0.00001	0.00001	9.96E-07	1.39E-05	0.00001	0.00001
cdd	-2.72E-06	-2.72E-06	-3.2E-05	-3.4E-05	-2.72E-06	-2.72E-06
h1_ reexp	-0.70909					
h2_ reexc		-16.40724				
h3_ipi			74.73***			
h4_poil				-2.27714		
h5_ nexcr					-6.590933	
h6_ ise100						-0.4175889

Notes: *, **, *** shows the statistical significance of coefficient at 10%, 5% and 1% significance levels.
[1]The series are cross sectional demeaned.

Table 9.2 Estimation Results of Electricity Demand Model for OECD Countries (Panel data on 27 OECD countries over the period from 1985 to 2007)

lnpcec	FGLSDV estimation (Static)	System GMM Estimation (Dynamic)	PMGE (ARDL based ECM)	CCE-MG Estimation (ECM)
			Long-run	**Long-run**
$lnpcec_{-1}$		0.78340***		
lnpcgdp	0.44919***	0.09428**	0.324***	0.32***
lnrep	-0.0856***	-0.07626***	-0.116***	-0.003
uratio	4.68415***	0.65639*	4.831***	0.19
h4_poil	-0.1402694	-0.04502	-0.018	
constant	0.87788***	0.84098***		
ECT			-0.559 ***	-0.62 ***
			Short-run	**Short-run**
$\Delta lnpcec_{-1}$			0.006	-0.15*
Δ lnpcgdp			0.070	0.68***
$\Delta lnpcgdp_{-1}$			-0.114*	-0.17
Δ lnrep			0.050	-0.03
$\Delta lnrep_{-1}$			-0.040	0.02
Δ uratio			7.493	-13.20
$\Delta uratio_{-1}$			4.928	-17.57
Δh4_poil			-1.018**	-0.09
Δ $h4\_poil_{-1}$			-0.187	-0.01
constant			1.456***	0.000035

Notes: *, **, *** shows the statistical significance of coefficient at 10%, 5% and 1% significance levels.

In B part of Table 9.1, we present the estimation results of dynamic panel data model estimated by system GMM employing different volatility measures. Income elasticity is estimated to be between 0.35 and 0.43 within range of previous study's findings, whereas price elasticity is found to be between -0.11 and -0.59 again in the interval of the elasticity estimates obtained by previous works. All the elasticity estimates are significant with theoretically congruent signs. Therefore, we can conclude that electricity demand is inelastic with respect to income and price. Our results are also supported by the past studies based on panel and time series data employing partial adjustment model, for example, Hsiao et al. (1989), Diabi (1998), Erdoğdu (2007), and Bhargava et al. (2009) have found that electricity demand is inelastic with respect to income and price. Besides, urbanization ratio and the only one volatility measure, namely, conditional variance of industrial production index growth are observed to affect electricity demand, significantly and positively.

In Table 9.2, the estimation result of the static model for a panel of OECD countries shows that all factors have significant impacts on electricity demand with theoretically expected signs except oil price volatility; and electricity demand is price and income inelastic. Based on static model, similar conclusion is obtained by the following studies: Soysal (1986), Kamerschen and Porter (2004), Atakhanova and Howie (2007), Contreras (2008), Issa and Bataineh (2009), Chaudhry (2010), and Fan and Hyndman (2011). Income and price elasticities are found to be 0.44 in the interval of elasticity estimates obtained by past studies and -0.08 out of range of previous findings. The dynamic models estimated differ according to the homogeneity of coefficients across countries, results are given in Table 9.2 for OECD countries. Dynamic panel data model estimated by system GMM assumes the homogeneous slopes and error variances, whereas, ARDL based ECM and ECM estimated by PMGE and CCE-MG, respectively, only assumes the homogeneity of long-run coefficients and allow heterogeneous intercepts, short run coefficients and error variances across countries. In the estimation results of dynamic panel data model, all the coefficients are significant with correct signs, however, oil price volatility is not a statistically significant determinant as in the static model. We can conclude that electricity demand is inelastic with respect to income and price in line with the findings of Murray et al. (1978), Diabi (1998), and Erdoğdu (2007). Income (price) elasticity is 0.094 (-0.076) in the interval of elasticity estimates previously obtained. By ARDL-based ECM estimated by PMGE allowing the intercepts, short run coefficients and error variances vary across the countries, however, restricting the long run coefficients to be same, we obtain similar results with the dynamic panel data model with slight differences. All the coefficients are found to be significant in the long run except the one associated with the oil price volatility variable, however, in the short run, we observe significant effects of only oil price volatility and one period lagged lnpcgdp, at 5% and 10% significance levels, respectively. Our finding is in agreement with the claim of Bredin et al. (2008) on the contractionary short run effect of oil price increases and decreases. Weiner (2005) also focused on the adverse effects of oil price volatility on the investment and the employment. The short run and the long run income (price) elasticities are estimated as 0.07 and 0.324 (0.05 and -0.116) conforming to the range of elasticity estimates reported by past works except positive short run price elasticity contrary to theoretical expectations as well as findings of previous studies. The significant and negative estimate of error correction term signifies a convergence to the equilibrium with an adjustment speed of 0.559 which means that 55.9% of the deviations from the long run equilibrium level of electricity consumption are corrected within an one year period after a shock. The long run and short run electricity demand is found to be inelastic with respect to income and price, however, in the long run, it is more responsive to changes in income and price. Carlos et al. (2009) have explained this finding as a result of recent increase in the autoproduction facilities for the industrial sector and replacement of electrical appliances, machines and equipments with the energy-efficient ones in the residential and industrial side. Previous literature reached the same conclusion, for example, Lundmark (2001), Al-Faris (2002) for Oman, Lin (2003), De Vita et al. (2006), Inglesi (2010), Sohaili (2010), Alter and Syed (2011), Bekhet and Othman (2011), Ekpo et al. (2011), and Zaman et al. (2012). According to the CCE-MG estimation result of ECM, in both the long run and the short run, only income is a significant determinant of electricity demand, while oil price volatility has negligible influence in the short run. However, long run and short run income elasticity is smaller than one indicating the inelastic electricity demand to changes in income. Moreover, in most of the estimations for both Turkey and OECD, the finding of lower elasticity of electricity consumption with respect to income can be a reflection of low energy intensity which is a sign of low level of energy requirement for the percentage increase in GDP reflecting the efficient use of electricity or economy's structural composition as pointed out by Atakhanova and Howie (2007) and Yépez-García et al. (2011). In section 10, we present the conclusions and the directions for future researches along with the policy recommendations.

CHAPTER 10

CONCLUSIONS, POLICY RECOMMENDATIONS, AND DIRECTIONS FOR FUTURE RESEARCHES

In this dissertation, we examine the determinants of electricity demand and the effect of economic volatility on the electricity demand. Our analysis is based on volatility modeling and panel data techniques. The study includes two panel data applications: one is for Turkey based on the data at the province level and the other is for the panel of OECD countries. In the estimations, we observe the importance of inclusion of dynamics into the model and the consideration of the unit root properties of the panel series and time series included in the analysis. In the application for Turkey, we employ different volatility measures obtained by using ARCH/GARCH models in order to check for the robustness of the results. The elasticity estimates show consistency over the estimations performed with various volatility measures. However, only the volatility related to the industrial production is found to have significant effects. For the panel of OECD countries, we find significant and adverse short run impact of oil price volatility on electricity consumption. Our result is parallel to the finding of Bloom (2009). In order to determine the impact of uncertainty shocks, Bloom (2009) developed a theoretical model and from the simulation of the model, he found that the increased volatility generates a rapid temporary slow-down in the economic activity in the short run; however, after this slow-down, activity bounces back to its initial level. Therefore, he pointed out that this asymmetric effect of economic shocks are temporary in contrast to the permanent symmetric effects of economic shocks. He explained the short run negative impact of uncertainty as a result of fixed capital stock in the short run; however, as, in the long run capital stock becomes variable, negative effect of uncertainty does not last. If possible, in order to avoid the adverse effects of volatility, one can reduce it. But for this, we need to explore the factors leading to the volatility. However, some volatility is unavoidable and exogenous. For example, some reasons of the oil price volatility are the political and economical instability in the oil producing countries and natural disasters and if the country (for example, US, Japan, Belgium, Italy, Germany, France, Turkey) is dependent on the imported oil very intensively in its economic activities, the negative impact of oil price volatility can be inevitable and severe. In this case, the country needs to decrease its external dependency on oil by exploring its own oil reserves, if possible; otherwise, the diversity of energy resources can be extended in order to substitute for oil and as Weiner (2005) and Pourshahabi et al. (2012) have suggested, diversification across oil exporting countries, keeping strategic petroleum reserves, and hedging can be another solutions to reduce the impact of oil price volatilities. One more solution can be the restructuring of the industrial sector to the less-energy intensive structure in the long term. Moreover, by the dissemination of the energy efficiency and conservation applications, as the share of energy spending decreases, external dependency and thus the effect of oil price volatility can diminish. For example, Cologni and Manera (2009) have showed that the effect of oil price volatility on output growth has mitigated over time as a result of energy efficiency improvements and better management of external supply and demand shocks by fiscal and monetary authorities although Chen and Hsu (2012) argued that energy efficiency is an ineffective tool for the mitigation of the negative impacts of oil price volatility on the international trade. Besides, in the future, by the extensive use of electrical automobiles, we expect the oil dependency in the transportation to decline. Rafiq et al. (2009) have suggested the subsidization of domestic oil price by the government in order to stabilize it and thus, mitigate the negative impacts of oil price volatility on employment, growth, and investment; but this leads price distortions and puts a huge burden on the government budget. On the other hand, Weiner (2005) stated that oil price volatility can be harmful to oil exporting countries as well due to the difficulty in managing the price spikes besides downward price movements. The investments in oil extraction industry and the investment decisions in physical capital on natural gas or oil can be affected according to Pindyck (2004) and Pourshahabi et al. (2012) as a result of the risk exposed by the increase in oil price volatility on the producers and industrial consumers. Kellogg (2010) also found that firms decrease drilling activities when the implied oil price volatility is higher.

Another important result of our analysis is that the electricity demand is found to be inelastic with respect to income and price both in the long run and the short run with theoretically consistent signs implying that electricity is a normal good and a necessity, but more responsive to price and income changes in the long run due to the time lag for the capital stock adjustment. The reason behind this is the fact that "electricity is indispensable in manufacturing and is regarded as essential to the quality of the life by most individuals in industrialized societies" (Kirschen, 2003: 521), as well as, electricity cost constitutes only small portions of total costs of firms and budget of households as pointed out by Kirschen (2003); further, Kirschen (2003) proposed some tools to encourage the active participation of demand side in order to increase the short run price elasticity leading to more efficient and competitive electricity markets, decrease in price spikes, and increase in energy supply security. In addition, other result is that the short run and long run income elasticities are observed to be higher than the price elasticities, supported by the results of Jamil and Ahmad (2011) partially, Erdoğdu (2007), and Akan and Tak (2003). These findings also have important policy implications. Only the huge electricity price increases can lead to the desirable demand reductions, however, this can conflict with the social policies such as supplying cheap and high quality electricity service to every citizen. Therefore, policies depend on electricity prices alone are not so much effective, especially in the short run to decrease electricity demand. As the electricity demand is more responsive in the long run, the pricing policies can be more effective in the longer term. Besides, as price elasticity is smaller than one, a small increase in prices can lead to large revenue increases for generation, distribution, transmission, retail, and wholesale companies. However, in order to avoid the exploitation of end-users, the tariffs of transmission, distribution, and retail sale are regulated, whereas, generation, retail sale, and wholesale segments are opened up to competition. Along with pricing policies such as time-of-use pricing, dynamic pricing, and interruptible tariff structure, following the policy suggestions of Bhargava et al. (2009), Narayan and Smyth (2009), Sa'ad (2009), Jamil and Ahmad (2010), and Jamil and Ahmad (2011), some of the energy policies on demand side and supply side to ensure the supply security as well as to meet the environmental standards can be listed as follows: implementation of regulations and information campaigns for the energy efficiency improvements covering all the sectors, mandatory energy efficiency standards for appliances and equipments, rationalizing the tariff structure for all sectors and across the regions by the abolishment of cross-subsidization across consumer classes and regions, campaigns and trainings to increase the consumer awareness on the energy waste, diversification of resources in electricity generation, utilization of renewable energy sources, generation capacity expansions, investments in transmission and distribution networks, implementation of policies, regulations, and technologies inducing reduction in the energy losses and illicit utilization in transmission and distribution as well as encouraging the efficiency improvements in the electricity generation, interregional electricity exchanges, encouragement of efficient autoproduction, policies for stimulating competition in the sector and private sector involvement, and construction of the regulatory framework that ensure credibility for the foreign and domestic investors in the electricity sector. In addition, as a support for the energy efficiency programs, Berry (2008) found that energy efficiency programs are successful on reducing the growth of power sales by 60% based on the comparison between the U.S. states in which aggressive efficiency programs are implemented and the ones without the implementation of such policies.

While formulating suitable energy policies, the last finding of our study that needs attention is the bidirectional long run and short run causality between electricity consumption and GDP for the panel of OECD countries implying simultaneous relation such that high level of income leads to the high level of electricity consumption, and vice versa. Before implementing the policies to reduce electricity consumption, its possible adverse effects on economic growth should be assessed by comparing the income elasticity of electricity consumption with the electricity consumption elasticity of income. However, some energy policies do not lead to such conflict such as generation capacity expansion and energy efficiency applications. According to Dobnik (2011), energy conservation based on the energy efficiency improvements rather trigger the economic growth through the productivity increase. In order to be compatible with the environmental policies, for the generation capacity expansion, higher share can be allocated to the environmentally friendly clean electricity generation technologies such as renewable energy and clean coal energy generation technologies. Another important implication of the bidirectional causality is the possibility of misleading forecasts of electricity consumption from single equation models without taking into account the endogeneity of income/GDP. Solutions to this problem can be the use of instrumental variables or the systems of equations model that allow for the feedback effects.

Although this study has some limitations, results of the study can be used for forecasting purposes, generation and transmission investment planning, evaluating environmental impacts of electricity consumption, and designing energy policies. As the electricity demand differs in the characteristics and the development across the sectors and within the sectors, an analysis based on household or firm level data will provide better and accurate information to policy makers, electric utilities, end-users, regulators, and other agents involved in the electricity sector. Another suggestions for the future researches are the consideration of the effect of the regulations, policies and programs on the electricity consumption as already mentioned by Paul et al. (2009). And also, employing different volatility measures can lead to interesting results.

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APPENDICES

Appendix 1. Figures

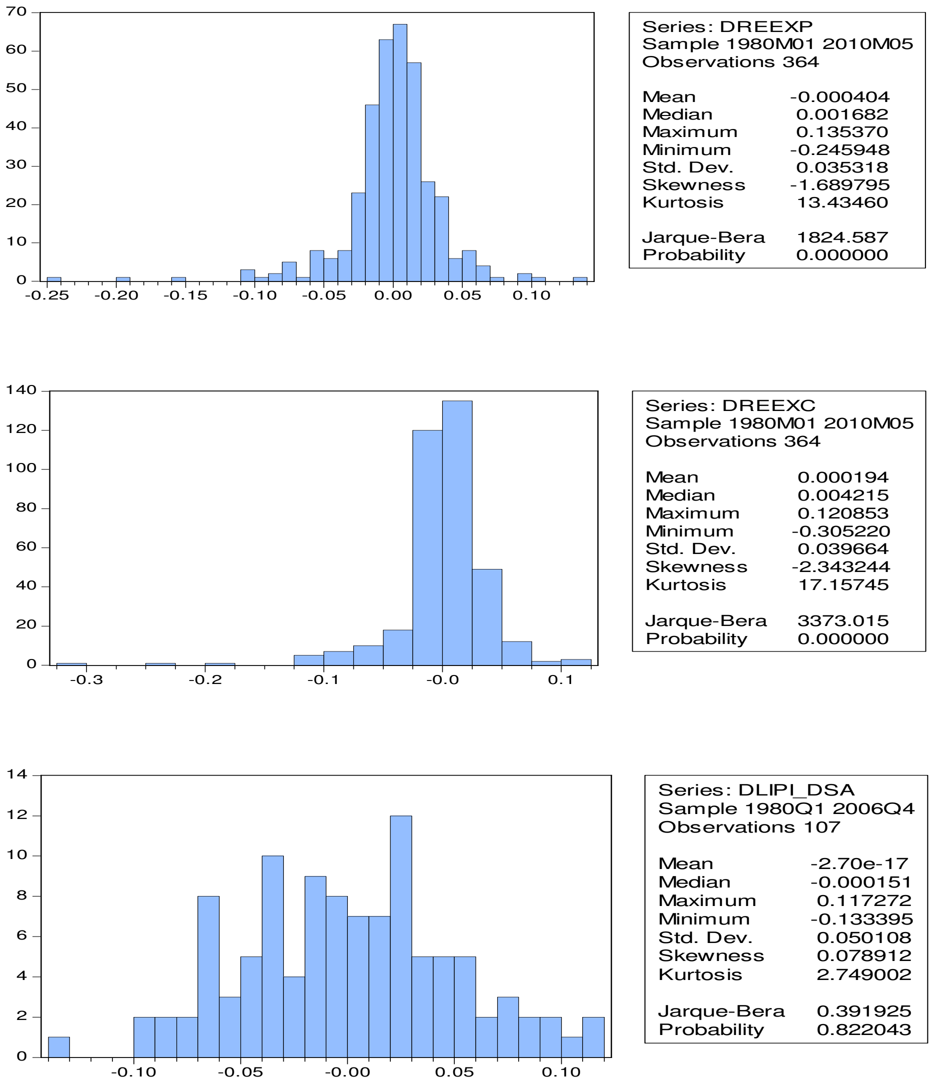
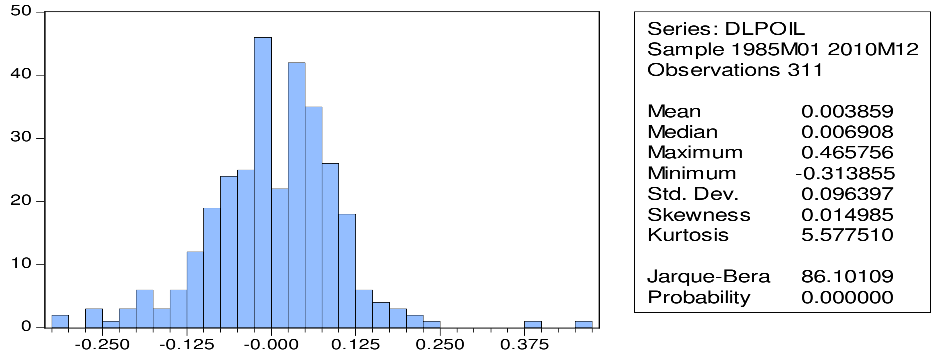
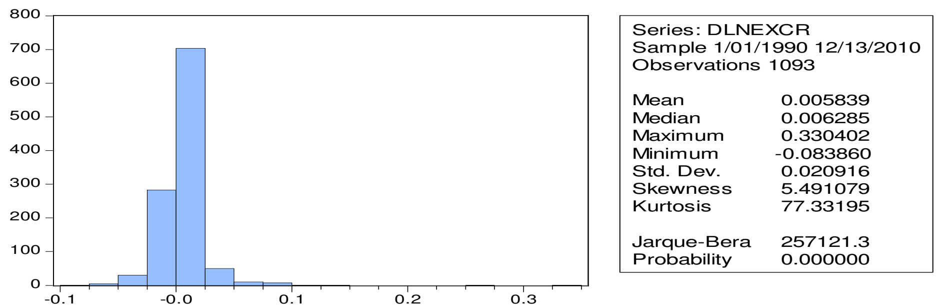


Figure A.1 Histograms and Summary statistics for logarithmic differenced Real Exchange Rate and Industrial Production Indices Series





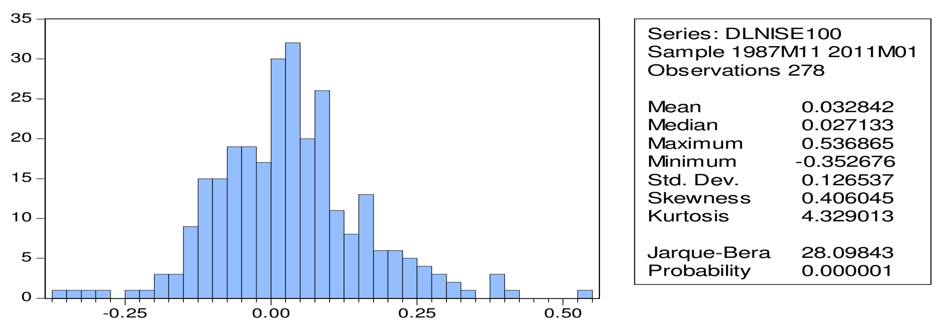
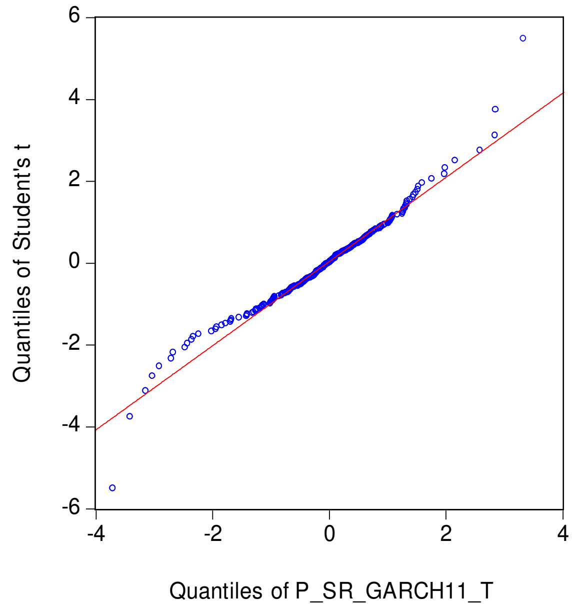


Figure A.2 Histograms and Summary statistics for logarithmic differenced Crude Oil Spot Price, Nominal Exchange Rate and ISE 100 Index Series



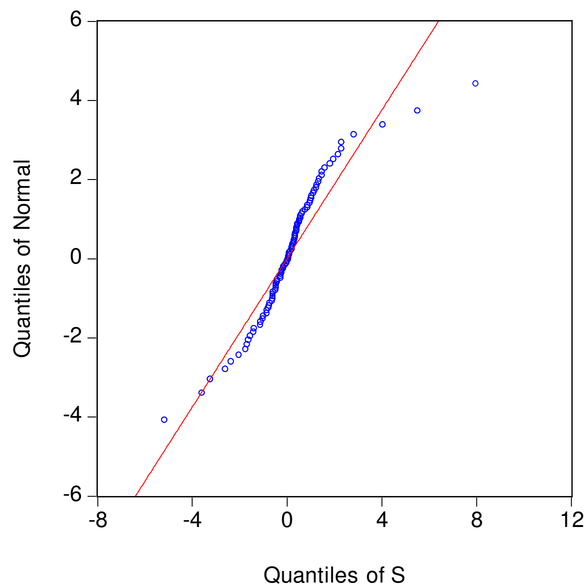
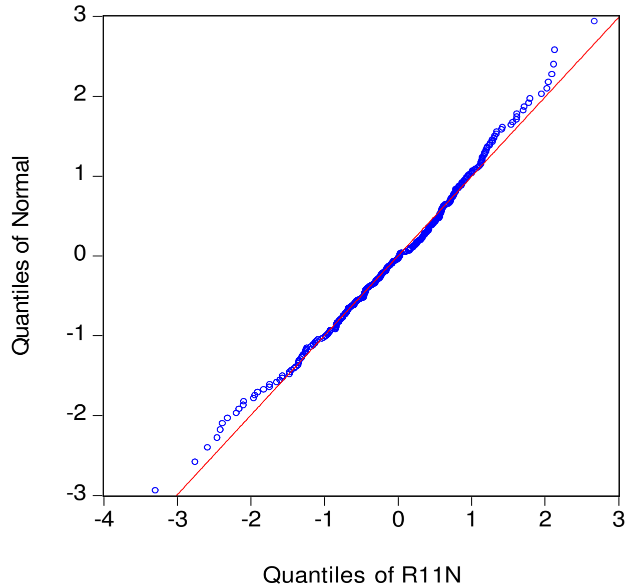


Figure A.3 Quantile-Quantile Graphs for the Residuals from the GARCH Model Estimations of logarithmic differenced Real Exchange Rate Index at Producer Prices and Industrial Production Index



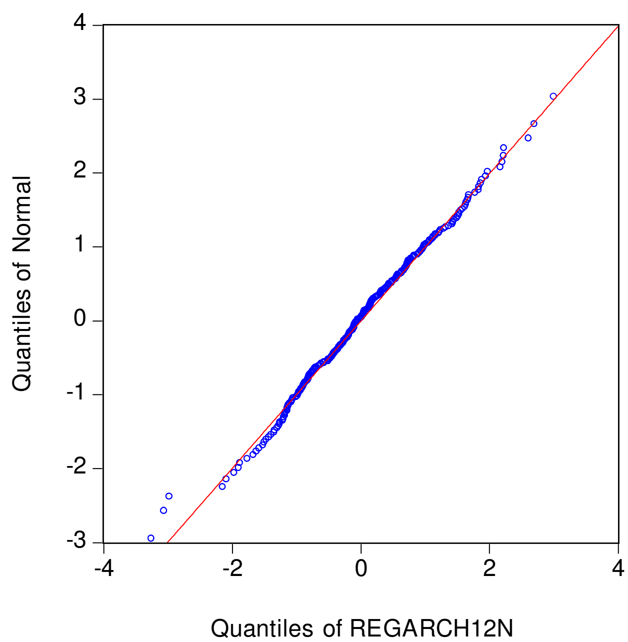


Figure A.4 Quantile-Quantile Graphs for the Residuals from the GARCH Model Estimations of logarithmic differenced Crude Oil Spot Price and ISE 100 Index Series

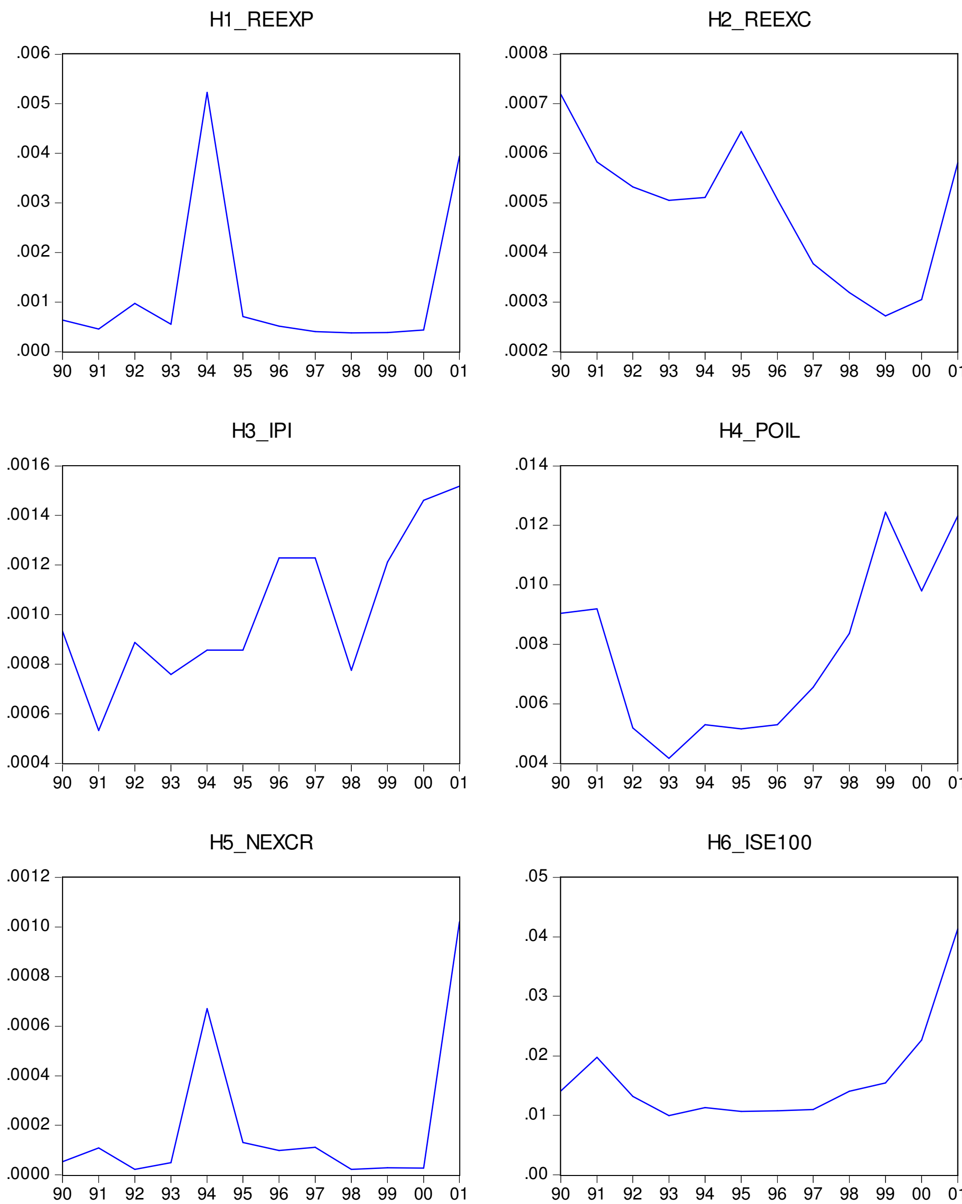


Figure A.5 Real Exchange Rate, Production, Oil Price, Nominal Exchange Rate and ISE 100 Volatility Series, 1990-2001

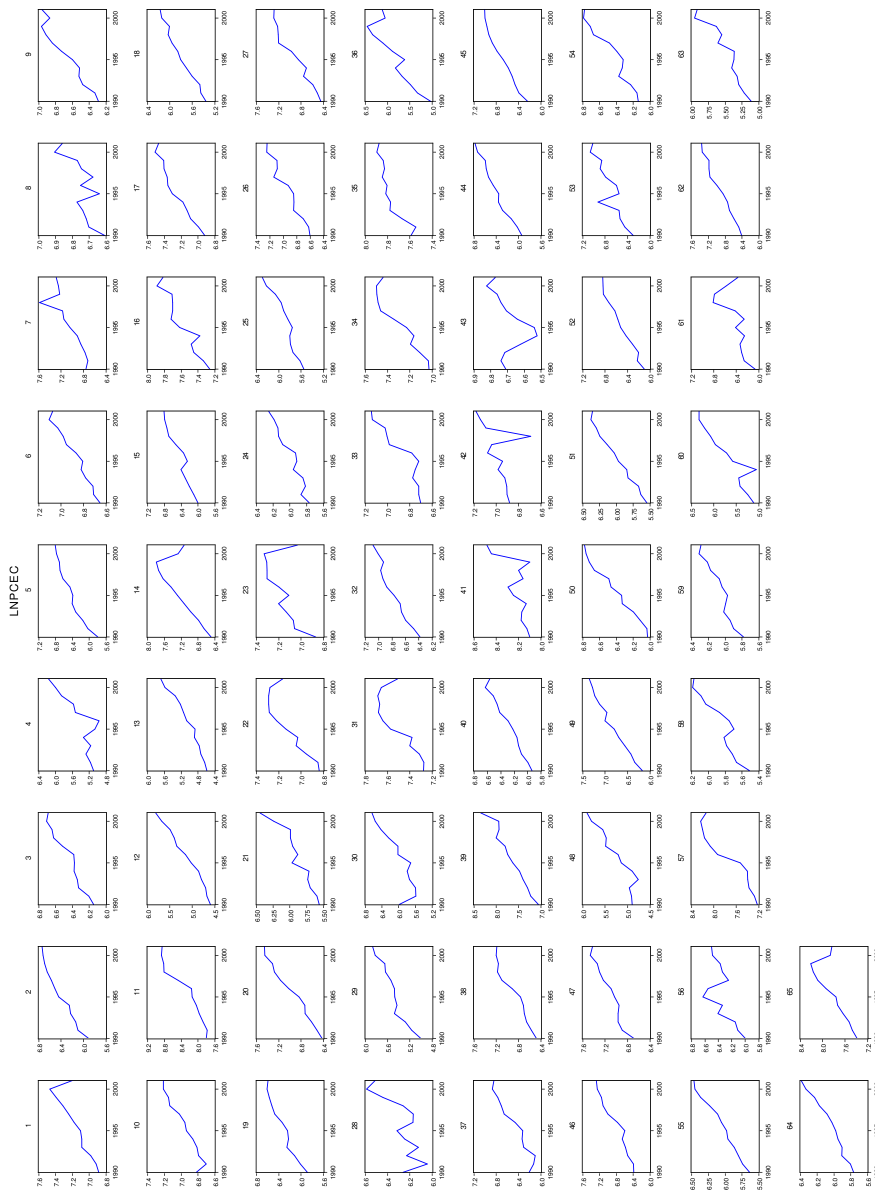


Figure A.6 Logarithm of per capita Electricity Consumption Series for Each Province of Turkey, 1990-2001

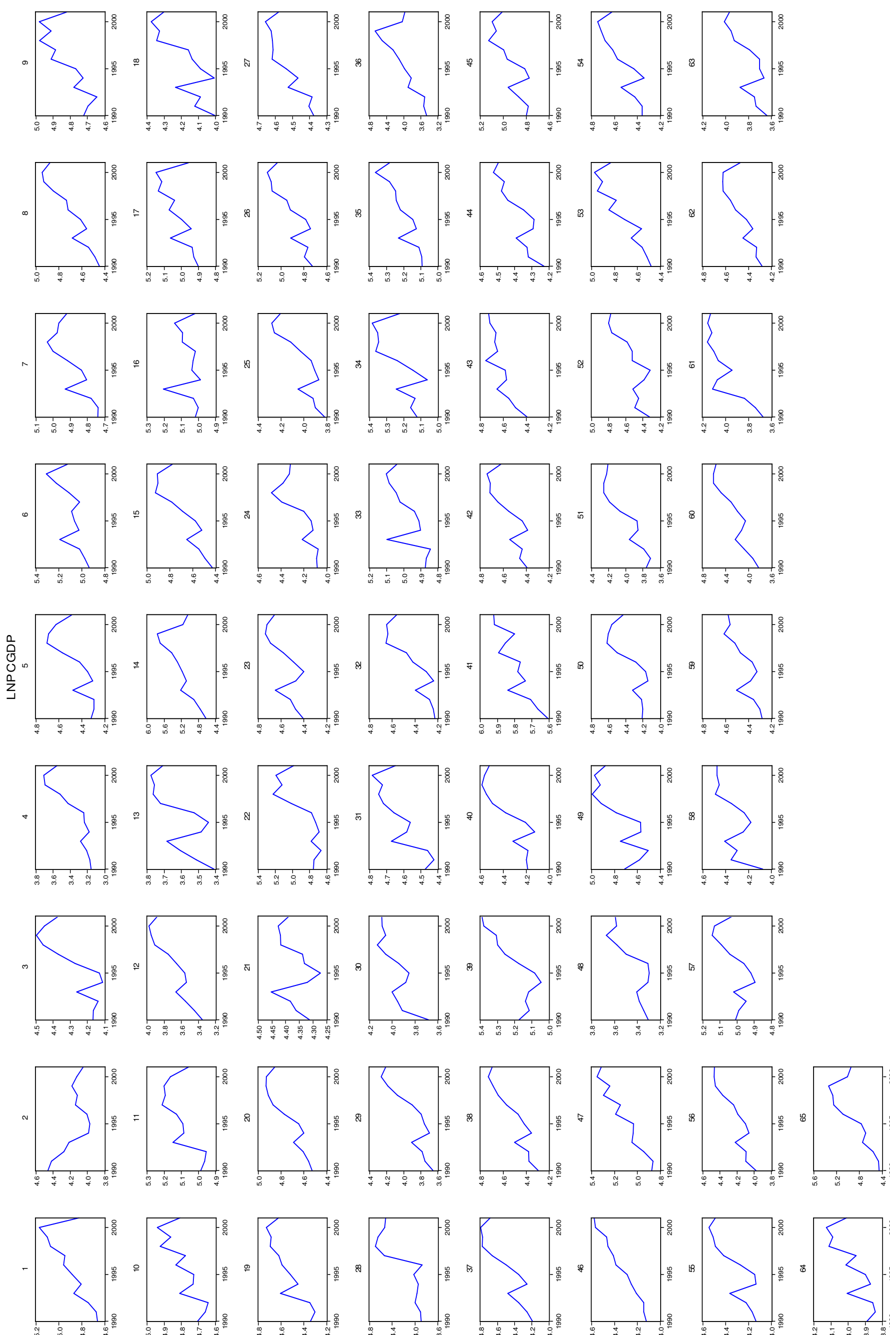


Figure A.7 Logarithm of per capita GDP Series for Each Province of Turkey, 1990-2001

Figure A.8 Logarithm of Real Electricity Price Series for Each Province of Turkey, 1990-2001

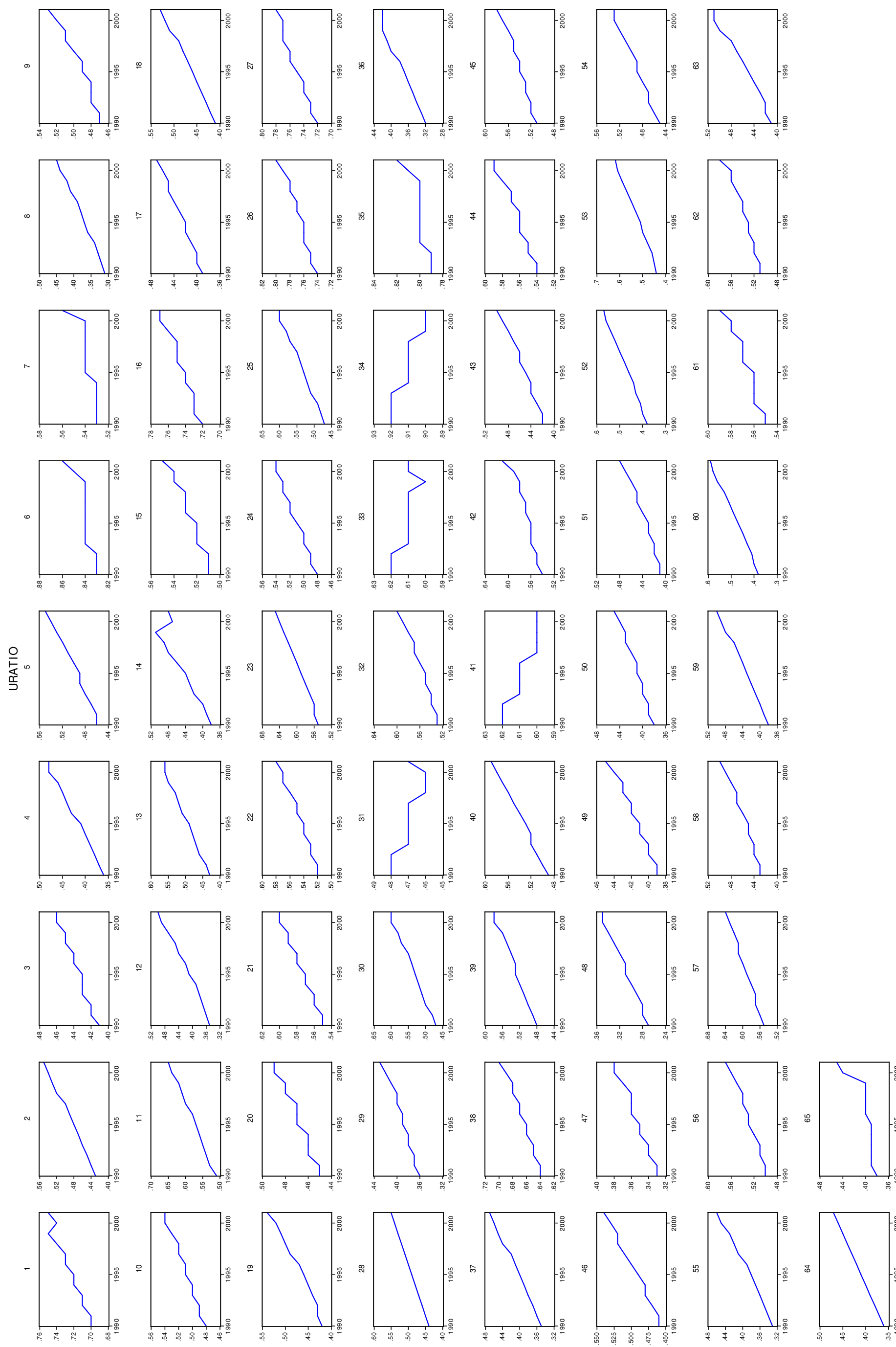


Figure A.9 Urbanization Ratio Series for Each Province of Turkey, 1990-2001

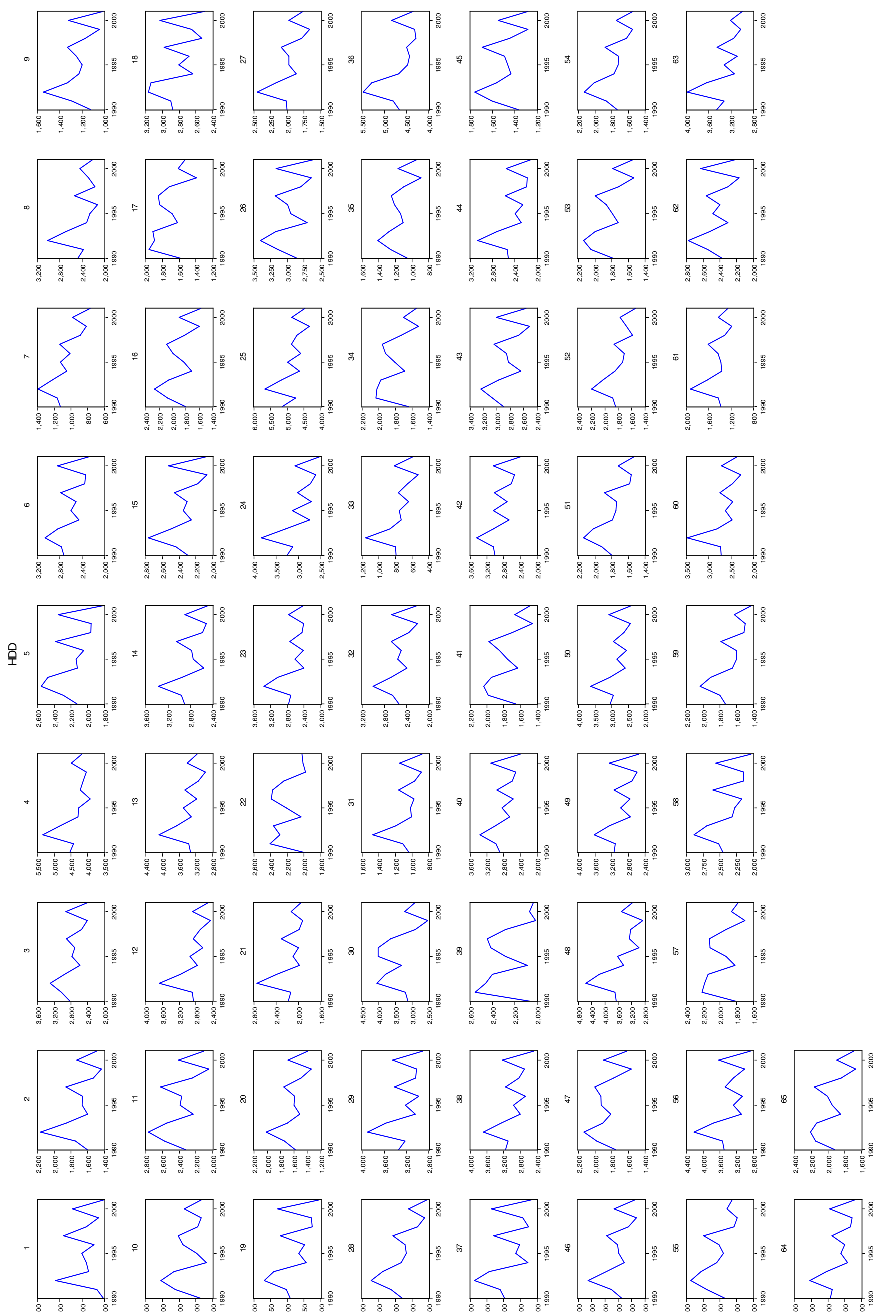


Figure A.10 Heating Degree Days Series for Each Province of Turkey, 1990-2001

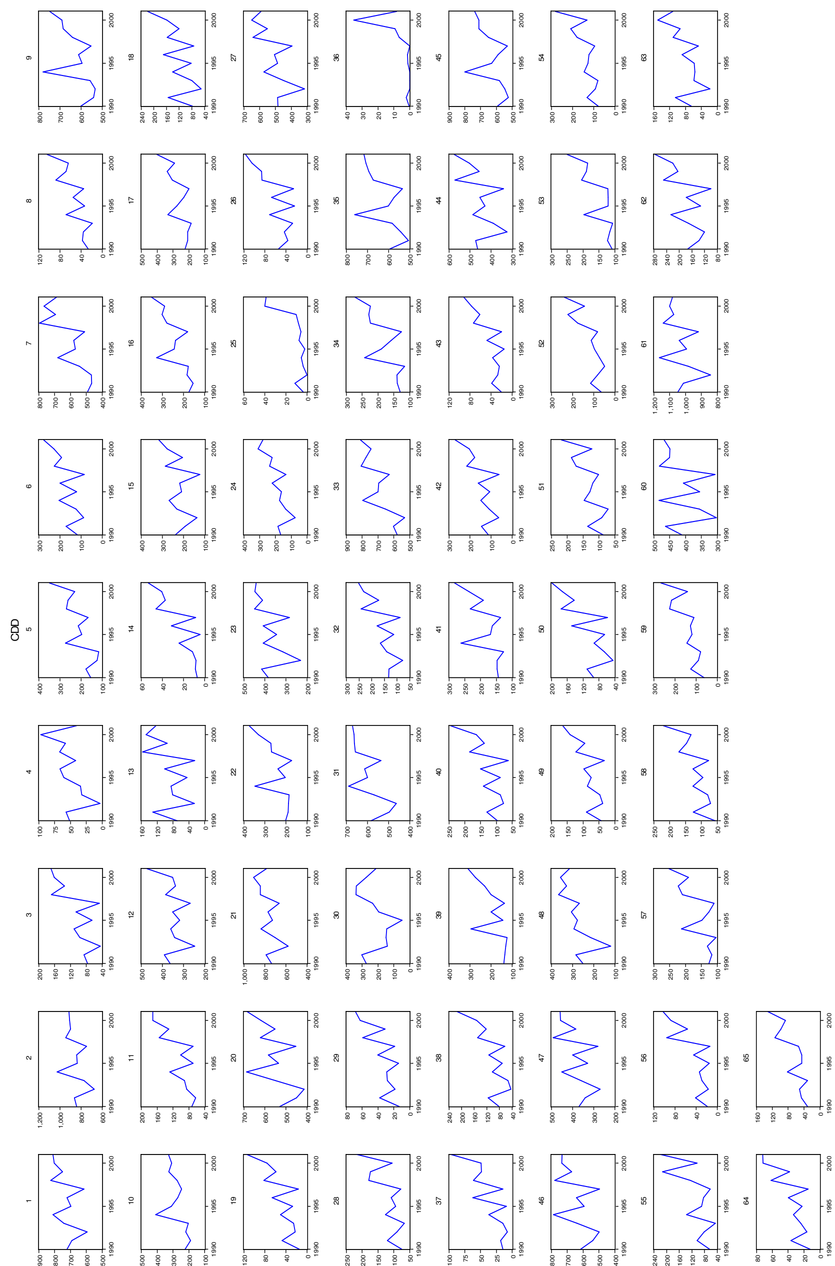


Figure A.11 Cooling Degree Days Series for Each Province of Turkey, 1990-2001

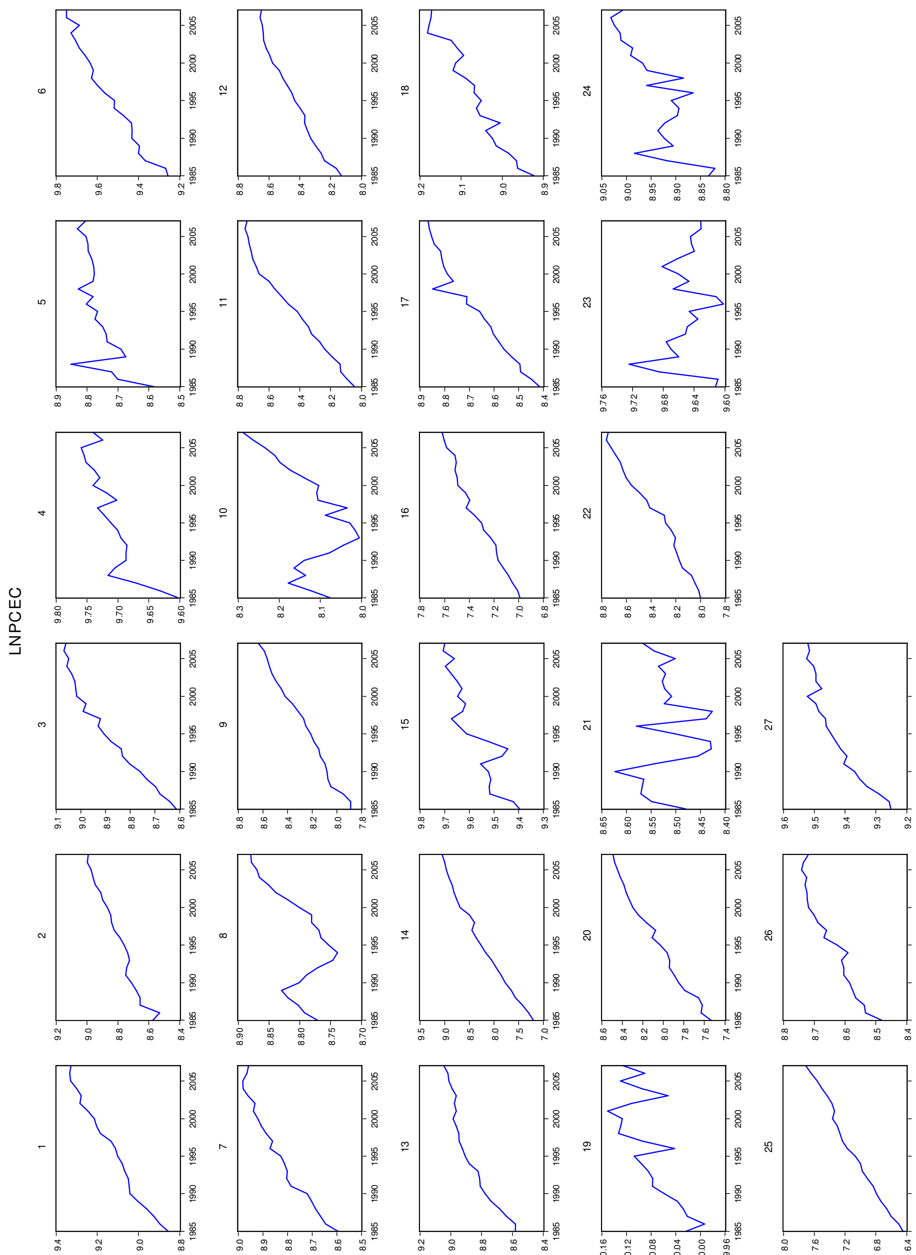


Figure A.12 Logarithm of per capita Electricity Consumption Series of Each Country, 1985-2007

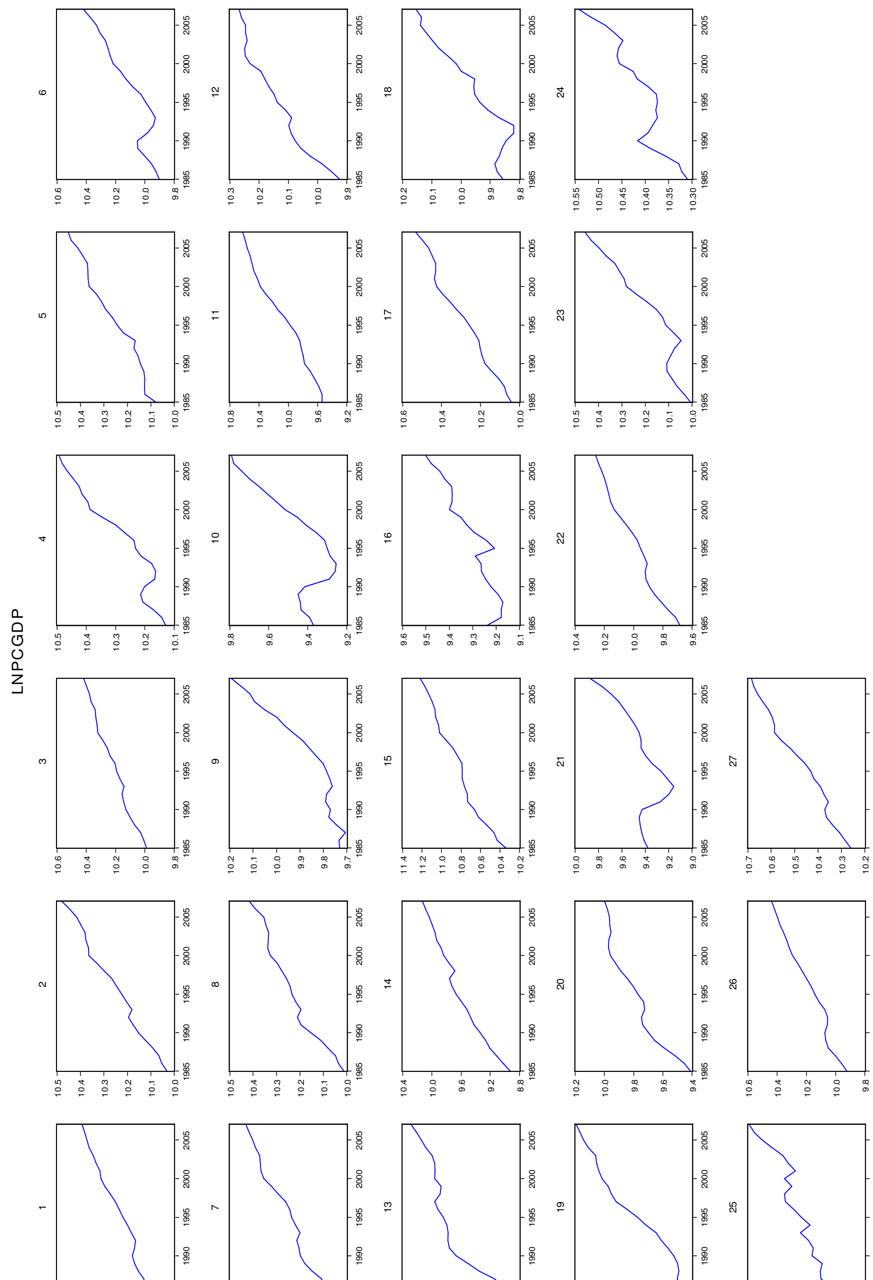


Figure A.13 Logarithm of per capita GDP Series of Each Country, 1985-2007

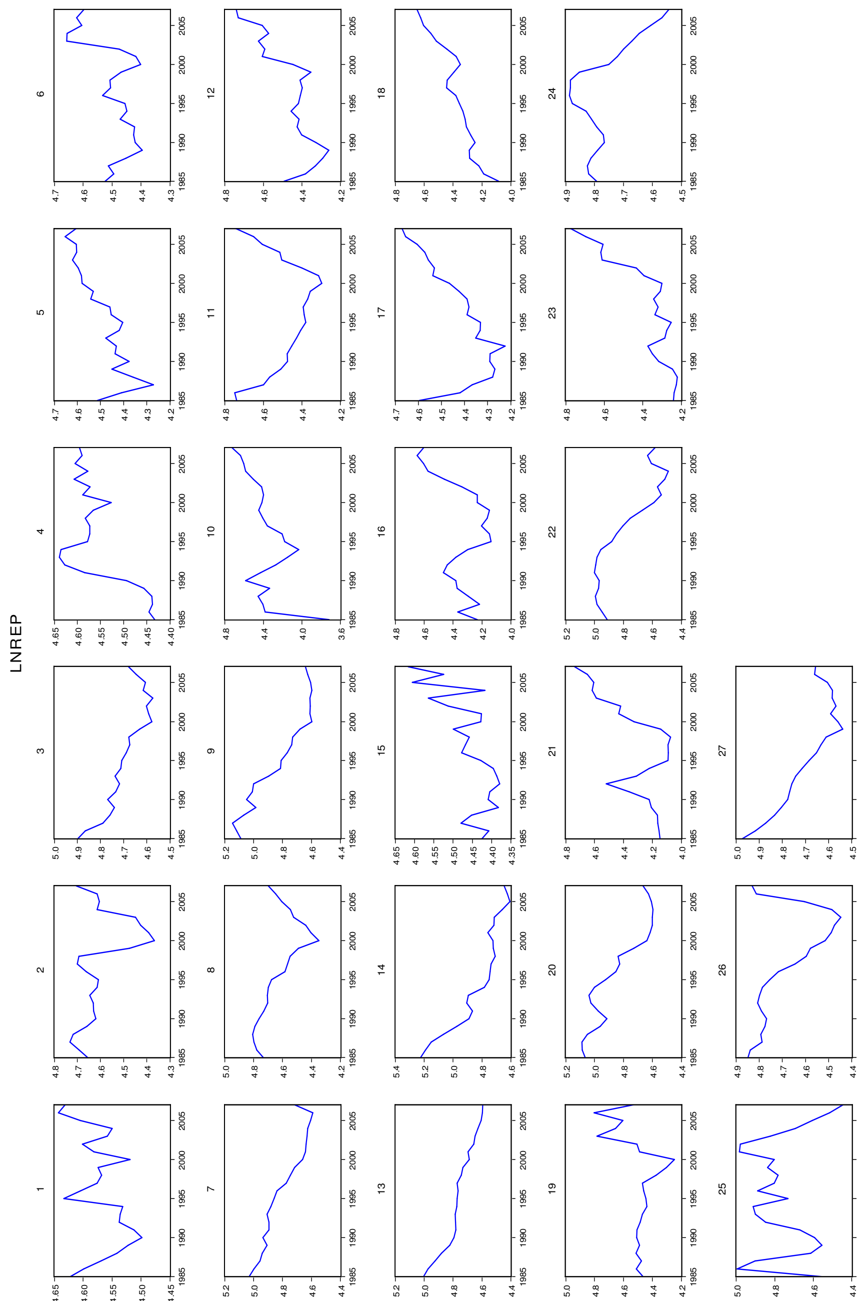


Figure A.14 Logarithm of Real Electricity Price Index Series of Each Country, 1985-2007

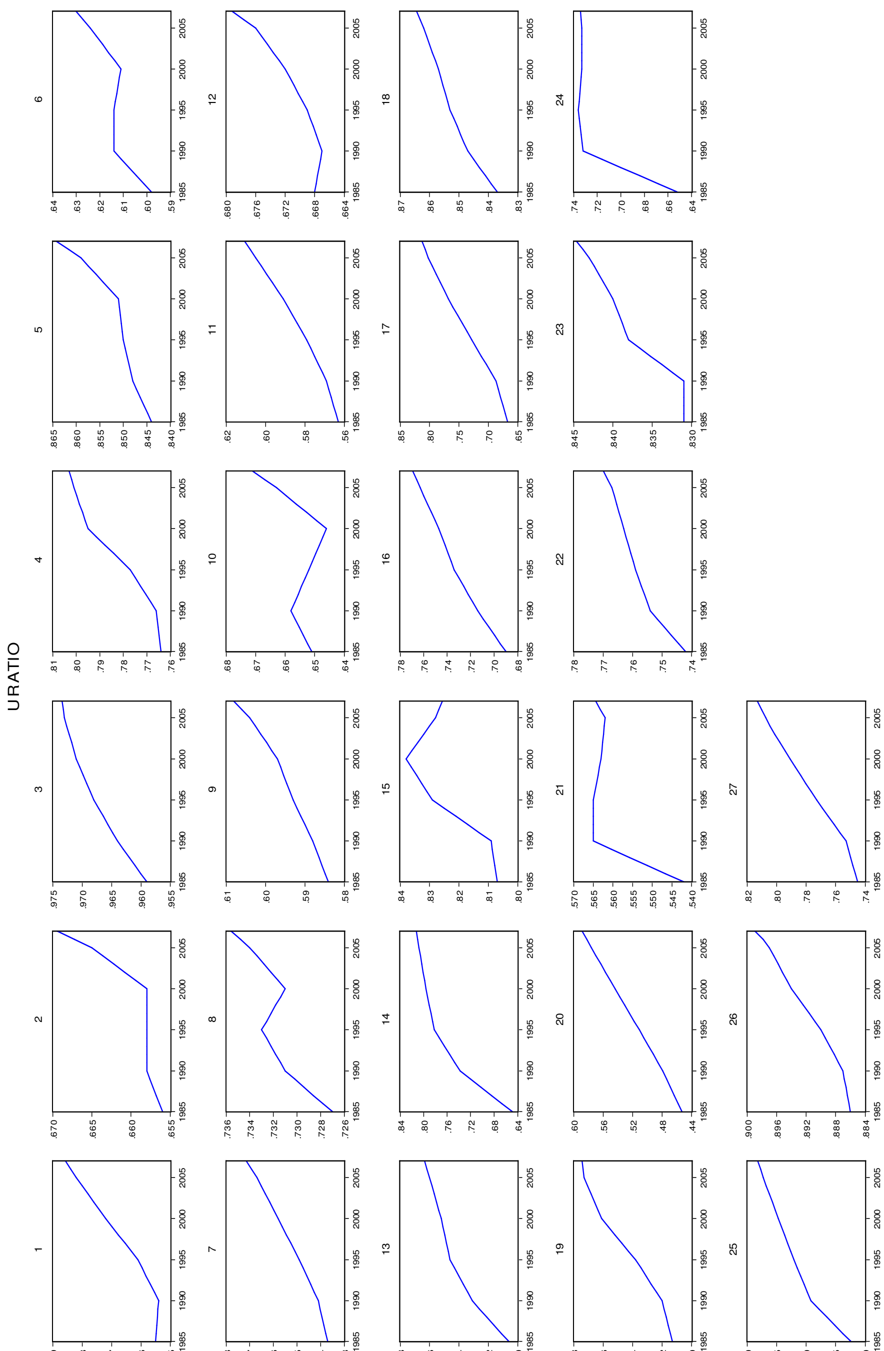


Figure A.15 Urbanization Ratio Series of Each Country, 1985-2007

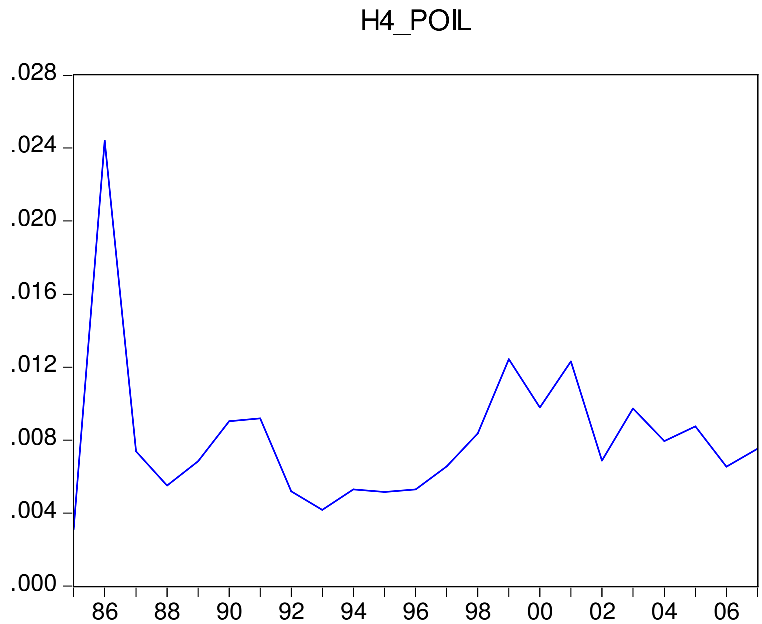


Figure A.16 Oil Price Volatility Series, 1985-2007

Appendix 2. First Generation Panel Unit Root Tests

We perform first generation panel unit root tests assuming cross-sectional independence of the series. The results are given in Table A.1. As can be seen from the Table A.1, first generation panel unit root tests lead to different conclusions.

For electricity consumption variable, IPS, Hadri, Choi ADF and PP tests indicate that the series is not stationary, while all tests except Hadri test suggest that the differenced series is stationary. Breitung, Hadri, PP Choi tests shows that income series is nonstationary and at 5% significance level, all test agree that differenced income series is stationary other than Hadri test. Electricity price series is stationary according to only two tests, namely, ADF-Fisher and PP-Fisher tests and again differenced series is shown to be stationary by all tests excluding Hadri test. Nonstationarity of urbanization ratio series is indicated by LLC, PP-Choi and Hadri tests and first difference is stationary according to all tests except Hadri, PP- Fisher Chi-square, ADF – Choi Z stat and PP – Choi Z stat tests.

Table A.1 First Generation Panel Unit Root Tests

Series in Level/Test	**lnpcec**	**lnpcgdp**	**Lnrep**	**uratio**
LLC	-1.36845* (0.0856)	-3.20585*** (0.0007)	0.10530 (0.5419)	0.09245 (0.5368)
Breitung	-3.37356*** (0.0004)	0.73458 (0.7687)	3.42774 (0.9997)	-13.5064*** (0.0000)
IPS	-1.15204 (0.1247)	-4.28605*** (0.0000)	-0.19172 (0.4240)	-5.37418*** (0.0000)
ADF - Fisher	85.7652*** (0.0038)	103.077*** (0.0001)	75.2297** (0.0297)	135.878*** (0.0000)
PP- Fisher	80.1197** (0.0120)	32.8125*** (0.0000)	116.014*** (0.0000)	108.972*** (0.0000)
ADF - Choi	-0.75930 (0.2238)	-4.10944*** (0.0000)	0.24846 (0.5981)	-2.15077** (0.0157)

Table A.1 (Continued)

PP - Choi	-0.07392 (0.4705)	1.77732 (0.9622)	0.61835 (0.7318)	0.05204 (0.5208)
Hadri Z-stat	10.4823*** (0.0000)	10.4373*** (0.0000)	8.22403*** (0.0000)	12.2907*** (0.0000)
Heteroscedastic Consistent Z-stat	8.46122*** (0.0000)	6.33599*** (0.0000)	7.96675*** (0.0000)	10.3857*** (0.0000)
First Difference/Test	**Δlnpcec**	**Δlnpcgdp**	**Δlnrep**	**Δuratio**
LLC	-14.4232*** (0.0000)	-5.19027*** (0.0000)	-10.0385*** (0.0000)	-43.5178*** (0.0000)
Breitung	-7.67760*** (0.0000)	-8.97753*** (0.0000)	-4.82902*** (0.0000)	-4.42687*** (0.0000)
IPS	-15.7386*** (0.0000)	-7.05273*** (0.0000)	-8.85578*** (0.0000)	-10.8718*** (0.0000)
ADF – Fisher Chi-square	298.566*** (0.0000)	140.659*** (0.0000)	179.381*** (0.0000)	80.4433*** (0.0069)
PP- Fisher Chi-square	980.475*** (0.0000)	119.411*** (0.0000)	498.996*** (0.0000)	13.9095 (1.0000)
ADF – Choi Z stat	-12.7681*** (0.0000)	-6.63843*** (0.0000)	-7.99929*** (0.0000)	0.92887 (0.8235)
PP - Choi Z stat	-22.5305*** (0.0000)	-5.36159*** (0.0000)	-13.3942*** (0.0000)	3.63920 (0.9999)
Hadri Z-stat	7.47555*** (0.0000)	2.02634** (0.0214)	6.23315*** (0.0000)	11.2366*** (0.0000)
Heteroscedastic Consistent Z-stat	16.6855*** (0.0000)	2.27581** (0.0114)	9.73057*** (0.0000)	11.4450*** (0.0000)

Note: The null hypothesis is that the series is a unit root process except for Hadri and Heteroscedastic Consistent unit root tests. An intercept and trend are included in the test equations. P values are provided in parentheses. Probabilities for Fisher-type tests were computed by using an asymptotic χ^2 distribution. All other tests assume asymptotic normality. The lag length was selected by using the Schwarz Information Criteria. For Newey-West bandwidth selection, Bartlett kernel was used. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%.

Appendix 3. Panel Unit Root Test with Structural Breaks

In order to analyze the presence of unit roots in the series with structural breaks, we also perform PANKPSS test proposed by Carrion-i-Silvestre et al. (2005). We consider the cases that allows for structural breaks in the intercept only for urbanization ratio series and in both intercept and trend for electricity consumption, income and electricity price series. Tables A.2 and A.3 present the results for series in level and in first differences.

Table A.2 Carrion-i-Silvestre et al. (2005) PANKPSS Tests Results for Series in Levels

Series/Countries	**lnpcec**	**lnpcgdp**	**lnrep**	**Uratio**
	KPSS	**KPSS**	**KPSS**	**KPSS**
Australia	0.279	0.393	0.227	1.582*
Austria	0.458	2.242***	0.342	1.908**
Belgium	0.093	0.206	0.051	2.712***
Canada	0.048	0.067	0.069	17.430***
Denmark	0.096	1.249	0.099	0.266
Finland	0.179	0.635	0.049	0.210
France	0.198	0.303	0.081	5.391***
Germany	2.459***	1.127*	0.931***	0.598
Greece	0.236**	0.174	2.060***	2.231***
Hungary	0.092	0.221	0.056	0.281
Ireland	0.257	2.285*	0.065	10.538***
Italy	2.941***	0.734*	0.687	0.327
Japan	0.655	0.053	0.143	6.694***
Korea, Rep.	0.063	0.364	0.843*	0.057
Luxembourg	0.564	1.634*	0.047	0.117
Mexico	0.397	0.206	0.089	9.997***
Netherlands	0.083	0.151	0.177	9.185***
New Zealand	0.069	0.044	0.576*	1.406***
Norway	0.105	0.308	0.149	0.936*
Portugal	0.258	1.700***	0.117	6.566***
Slovak Rep.	0.101	0.332	0.047	0.326

Table A.2 (Continued)

Series/Countries		lnpcec	lnpcgdp	lnrep	Uratio
		KPSS	**KPSS**	**KPSS**	**KPSS**
Spain		0.239	0.449	0.539	18.999***
Sweden		0.119	1.024	0.044	0.534
Switzerland		0.343	0.066	0.048	0.211
Turkey		0.199	0.096	0.038	7.231***
U.K.		0.065	0.142	0.860*	7.804***
U.S.		0.114	1.134	0.437	11.632***
		PANEL DATA TESTS			
Series		**lnpcec**	**lnpcgdp**	**lnrep**	**uratio**
No breaks (homogeneous)		4.797 (0.000)	21.245 (0.000)	4.298 (0.000)	133.824 (0.000)
B.C.V.	10%	10.053	13.396	10.125	22.940
	5%	11.706	16.868	11.744	31.909
	1%	15.010	25.027	15.316	53.245
No breaks (heterogeneous)		23.402 (0.000)	36.185 (0.000)	17.582 (0.000)	109.762 (0.000)
B.C.V.	10%	24.983	26.518	24.478	32.218
	5%	29.715	32.273	28.966	43.155
	1%	42.172	49.667	38.877	73.186
Breaks (homogeneous)		36.057 (0.000)	55.459 (0.000)	31.586 (0.000)	8.371 (0.000)
B.C.V.	10%	27.769	78.116	29.876	31.326
	5%	30.980	90.818	33.468	37.839
	1%	38.386	121.228	41.244	52.222
Breaks (heterogeneous)		88.424 (0.000)	363.247 (0.000)	92.907 (0.000)	579.306 (0.000)
B.C.V.	10%	107.076	459.727	123.190	65.988
	5%	120.465	517.929	139.409	73.888
	1%	150.464	621.687	176.395	93.964

Note: The number of breaks (m) is determined according to LWZ information criteria (modified SIC) for the models with breaks in intercept and trend; and for models with breaks in intercept only, selection of m is based on sequentially computed *pseudo* F-type test statistics. Maximum m is taken as 5. The long-run variance is estimated using Bartlett spectral kernel with automatic spectral window bandwidth selection. 2,000 replications are performed in the bootstrap distribution. Asymptotic P values obtained under the assumption of no cross-sectional dependence are provided in parentheses. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%. B.C.V. is abbreviation for Bootstrap Critical Values

In the tables, results of Hadri unit root test under the assumptions of no structural breaks and cross-sectional dependence/independence are also given. We deal with the problem of cross-sectional dependence by calculating the bootstrap distributions of the statistics. Statistics are computed for both assumptions of homogeneous and heterogeneous long run variance estimate. Under the assumption of cross-sectional independence regardless of the allowance for structural breaks, null hypothesis of stationarity for all the series in levels is rejected. But when we concern the cross-sectional dependence of the statistics, allowing for structural breaks leads to different conclusions. For electricity consumption series, if we employ test equation with breaks in intercept and trend using homogeneous long run variance estimate, test shows that the series is nonstationary at 5% significance level. The ignorance of structural breaks in income series causes the tests to indicate that series is nonstationary at 5% significance level. However, allowing for breaks in the test equations of electricity price series under homogeneous variance assumption lead us to reject the null of stationarity at significance level of 10%. And urbanization ratio series is found to be nonstationarity at 1% significance level using heterogeneous long run variance estimate. As a result, we can conclude that income series is stationary around a breaking trend when we account for cross-sectional dependence; for other series, conclusion depends on the assumption regarding to the homogeneity of long-run variance estimate.

Table A.3 Carrion-i-Silvestre et al. (2005) PANKPSS Tests Results for Series in First Differences

Series/Countries	**Δlnpcec**	**Δlnpcgdp**	**Δlnrep**	**Δuratio**
	KPSS	**KPSS**	**KPSS**	**KPSS**
Australia	0.078	0.252	0.071	0.1672**
Austria	0.155	0.046	0.219**	0.1717**
Belgium	0.154	0.057	0.106	0.2691***
Canada	0.241	0.096	0.071	0.1578**
Denmark	1.109**	0.085	0.294	0.1727**
Finland	0.14	0.207	0.427*	0.1619**
France	0.224	0.046	0.382*	0.1504**
Germany	2.118***	0.047	0.057	0.1496**
Greece	0.1	0.408	0.184	0.173**

Table A.3 (Continued)

Series/Countries		Δlnpcec	Δlnpcgdp	Δlnrep	Δuratio
Hungary		0.155	0.101	0.236	0.1596**
Ireland		0.343*	0.055	0.092	0.1511**
Italy		0.12	0.044	0.064	0.1122
Japan		0.105	0.129	0.133	0.1601**
Korea, Rep.		1.161***	0.083	0.107	0.1631**
Luxembourg		0.089	0.457*	0.817**	0.1396*
Mexico		0.146	0.076	0.193	0.1392*
Netherlands		0.097	0.064	0.278	0.164**
New Zealand		0.067	0.904	0.08	0.1694**
Norway		0.749**	1.147***	0.006	0.1732**
Portugal		0.145	0.87**	0.301***	0.1642**
Slovak Rep.		1.474***	1.231***	0.138	0.1633**
Spain		0.138	0.122	0.11	0.1662**
Sweden		0.16	0.273*	0.077	0.098
Switzerland		0.101	0.388	0.555**	0.1556**
Turkey		0.085	0.114	0.068	0.1491**
U.K.		0.121	3.038***	0.047	0.1308*
U.S.		0.081	0.05	0.091	0.1529**
PANEL DATA TESTS					
No breaks (homogeneous)		9.589 (0.000)	3.908 (0.000)	-0.330 (0.629)	-0.857 (0.804)
B.C.V.	10% 5% 1%	10.12 11.56 14.338	10.673 12.344 16.609	10.762 12.509 16.952	22.297 32.351 58.018
No breaks (heterogeneous)		18.032 (0.000)	12.859 (0.000)	13.710 (0.000)	25.419 (0.000)
B.C.V.	10% 5% 1%	26.364 30.444 40.306	28.495 33.873 51.018	26.639 30.619 39.972	37.111 48.989 86.178
Breaks (homogeneous)		10.665 (0.000)	10.808 (0.000)	-3.114 (0.999)	NA
B.C.V.	10% 5% 1%	11.150 12.641 15.281	13.051 14.667 17.681	13.333 14.807 17.539	
Breaks (heterogeneous)		40.163 (0.000)	57.971 (0.000)	19.852 (0.000)	NA
B.C.V.	10% 5% 1%	28.977 32.504 42.160	36.937 41.925 53.164	28.625 32.896 42.253	

Note: The number of breaks (m) is determined according to LWZ information criteria (modified SIC) for the models with breaks in intercept and trend; and for models with breaks in intercept only, selection of m is based on sequentially computed *pseudo* F-type test statistics. Maximum m is taken as 5. The long-run variance is estimated using Bartlett spectral kernel with automatic spectral window bandwidth selection. 2,000 replications are performed in the bootstrap distribution. Asymptotic P values obtained under the assumption of no cross-sectional dependence are provided in parentheses. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%. B.C.V. is abbreviation for Bootstrap Critical Values

From the results of tests for series in first differences concerning cross-sectional dependence of statistics but not the structural break, we can infer that the first differenced series under consideration is stationary both under the assumption of homogeneous and heterogeneous long run variance. If we account for breaks in addition to cross-sectional dependence of statistics, different results are obtained depending on the assumption regarding to the homogeneity of long run variance. If we assume homogeneous long run variance, the first differenced series appear to be stationary but heterogeneous long run variance assumption lead us reject the stationarity of first differenced electricity consumption and income series.

Appendix 4. First Generation Panel Cointegration Tests

Tables A.4 and A.5 show the results of the panel cointegration tests which are performed under the assumption of cross-sectional independence. Pedroni (1999, 2004) cointegration test statistics lead to different conclusions in panel cointegration tests (within-dimension). But there is much more consensus among the group mean tests (between dimension) about the strong evidence in favor of cointegration. And as Pedroni (1999) mentioned, incorrect imposition of common cointegrating vector assumption can cause misleading results such that one may not detect the presence of cointegration, in fact it exists. Therefore, we can rely on the results obtained from group mean tests. Panel B of Table A.4 shows the results of Kao (1999) cointegration test. The test rejects null of no cointegration at 10% significance level.

Combined Individual panel cointegration test (Fisher/Johansen) results are presented in Table A.5. Fisher statistics based on Trace test and Maximum Eigenvalue test for all specifications indicate that there are no any cointegration relations among electricity consumption, income, electricity price, and urbanization ratio variables; and infact tests show that cointegrating vector has full rank, thus all the variables are stationary. However, this result contradicts with some of the unit root tests.

Table A.4 Pedroni (1999, 2004) and Kao (1999) Residual-based Cointegration Test

A. Pedroni (1999, 2004) Residual-based Cointegration Test						
Panel Tests	**No deterministic[1] component**		**Only intercept[2]**		**Intercept+ trend[3]**	
v-Statistic	-0.952	(0.25)	-0.418	(0.37)	-0.328	(0.38)
ρ-Statistic	0.053	(0.40)	-0.286	(0.38)	0.241	(0.39)

Table A.4 (Continued)

A. Pedroni (1999, 2004) Residual-based Cointegration Test			
	No deterministic[1] component	**Only intercept[2]**	**Intercept+ trend[3]**
t-Statistic (PP - non-parametric)	-2.302** (0.03)	-4.753*** (0.00)	-10.12*** (0.00)
t-Statistic (ADF - parametric)	-3.05*** (0.00)	-4.150*** (0.00)	-8.831*** (0.00)
<u>Group Mean Tests</u> ρ-Statistic	1.169 (0.20)	0.870 (0.27)	2.002* (0.05)
t-Statistic (PP - non-parametric)	-3.870*** (0.00)	-7.390*** (0.00)	-17.7*** (0.00)
t-Statistic (ADF - parametric)	-4.633*** (0.00)	-7.563*** (0.00)	-10.9*** (0.00)
B. Kao (1999) Residual-based Cointegration Test[4]			
t-Statistic (ADF)	-1.643* (0.05)		

Note: The null hypothesis is that there is no cointegration. Under alternative hypothesis of Pedroni tests; common AR coefficient is assumed for all countries in panel tests; however, group mean tests allow for heterogeneity across countries. P-values are provided in parentheses. The lag lengths (p) are selected according to Schwarz information criterion. Maximum lag length for cross-section i is computed as $[\min(12, \frac{T_i}{3})(\frac{T_i}{100})^{0.25}]$, where T_i shows the time dimension of the cross-section *i*. For Newey-West bandwidth selection, Bartlett kernel was used. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%.

[1] The first stage estimation results employing mean group estimator are given as below;

$$\widehat{lnpcec}_{it} \ = \ 0.72 * \ lnpcgdp_{it} - 0.09 * lnrep_{it} + 2.95 * uratio_{it}$$

[2] The first stage estimation results employing mean group estimator are given as below;

$$\widehat{lnpcec}_{it} \ = \ 1.93 + 0.58 * \ lnpcgdp_{it} - 0.06 * lnrep_{it} + 1.74 * uratio_{it}$$

[3] The first stage estimation results employing mean group estimator are given as below;

$$\widehat{lnpcec}_{it} \ = \ 8.02 + 0.02 * t + 0.27 * \ lnpcgdp_{it} - 0.06 * lnrep_{it} - 2.70 * uratio_{it}$$

[4]Kao (1999) assumes that first stage regression includes cross-section specific intercepts and imposes homogeneous coefficients on the regressors in the first stage regression. The first stage estimation results are given as follows;

$$\widehat{lnpcec}_{it} \ = \ 1.45 + 0.56 * \ lnpcgdp_{it} - 0.27 * lnrep_{it} + 3.72 * uratio_{it} + \sum_{i=2}^{27} \mu_i \, D_{it}$$

Table A.5 Combined Individual Panel Cointegration Test (Fisher/Johansen)

			Number of Cointegration Relation			
			None	**At most 1**	**At most 2**	**At most 3**
Fisher Statistics	**S1**[1]	Trace Test	625.8*** (0.0000)	340.9*** (0.0000)	184.2*** (0.0000)	108.7*** (0.0000)
		Max Eigenvalue Test	421.5*** (0.0000)	235.5*** (0.0000)	144.8*** (0.0000)	108.7*** (0.0000)
	S2[1]	Trace Test	1008.0*** (0.0000)	550.5*** (0.0000)	278.1*** (0.0000)	164.4*** (0.0000)
		Max Eigenvalue Test	609.8*** (0.0000)	273.4*** (0.0000)	189.3*** (0.0000)	164.4*** (0.0000)
	S3[1]	Trace Test	853.3*** (0.0000)	409.9*** (0.0000)	235.9*** (0.0000)	156.9*** (0.0000)
		Max Eigenvalue Test	587.2*** (0.0000)	249.5*** (0.0000)	181.6*** (0.0000)	156.9*** (0.0000)
	S4[1]	Trace Test	1085.0*** (0.0000)	555.4*** (0.0000)	298.4*** (0.0000)	159.2*** (0.0000)
		Max Eigenvalue Test	1308.0*** (0.0000)	328.8*** (0.0000)	185.6*** (0.0000)	159.2*** (0.0000)
	S5[1]	Trace Test	974.0*** (0.0000)	477.3*** (0.0000)	233.2*** (0.0000)	161.9*** (0.0000)
		Max Eigenvalue Test	692.7*** (0.0000)	316.6*** (0.0000)	177.5*** (0.0000)	161.9*** (0.0000)

[1]Deterministic trend specifications are as follows; S1: No intercept or trend in cointegration equation (CE) or VAR (No trend in data); S2:Intercept in CE but no intercept in VAR (No trend in data); S3: Intercept in CE and VAR (Linear trend in data); S4: Intercept and trend in CE and no trend in VAR (Linear trend in data); S5: Intercept and trend in CE and linear trend in VAR (Quadratic trend in data). Lag number is taken as 2 for all countries because of small time dimension (T=23). Similar results are obtained using 1 lag except for maximum eigenvalue and trace tests in the specifications 1 and 4, such that, tests show the evidence of three cointegrating relations at 1% and 5% significance levels, respectively. P-values provided in parentheses are computed using asymptotic χ^2 distribution. *, **, *** shows the statistical significance of test statistic at 10%, 5% and 1%.

Appendix 5. Curriculum Vitae

PERSONAL INFORMATION

Surname, Name	**:**	Akarsu, Gülsüm
Nationality	**:**	Turkish (TC)
Date and Place of Birth	**:**	29.07.1981, Germany
Marital Status	**:**	Single
E-mail	**:**	gulsum.akarsu@yahoo.com, akarsu@metu.edu.tr

EDUCATION

Degree	**Institution**	**Year of Graduation**
BA	Ege University, Economics, İzmir	2003
High School	Özel Fatih Fen High School, İzmir	1999

WORK EXPERIENCE

Year	**Place**	**Enrollment**
2004- Present	METU, Economics Department	Research/Teaching Assistant

FOREIGN LANGUAGES

Turkish, native; English, fluent; and German, beginner level

PUBLICATIONS

Bali, T. Z., Erbaş, B. Ç., Akın, Z., and Akarsu, G. (2012) "Bir Sosyal Fayda/Maliyet Analizi: Soma-A Santrali Özelinde Kömür ve Rüzgar Alternatifleri", İktisat İşletme ve Finans, 27 (311), 41-82

COMPUTER SKILLS

Microsoft Office 2010, E-views Econometrics Package Program, RATS 6.01, Stata 11, and RETScreen.

AREAS OF RESEARCH INTEREST

Microeconomics, Financial Economics, Econometrics, Energy Economics, Linear and Nonlinear Time Series Analysis

Appendix 6. Turkish Summary

Enerji tüketimi, bütün dünya genelinde nüfus artışı, ekonomik büyüme, şehirleşme ve sanayileşmedeki artış gibi etmenlerden dolayı hızlı bir şekilde artmaktadır. 2013 yılında BP tarafından yayınlanan enerji raporuna göre, dünya birincil enerji tüketimi, 2011-2030 yılları arasındaki dönemde yıllık olarak %1,6 oranında artması ve bu artışın %93'ünün OECD dışı ülkelerde gerçekleşmesi beklenmektedir. 2010-2011 yılları arasında gerçekleşen dünya birincil enerji tüketimi artış oranı %2,5 düzeyindedir (BP, 2012). Aynı dönemde, OECD ve OECD-dışı ülkelerde büyüme oranları sırasıyla %-0,8 ve %5,3 olarak gerçekleşmiştir. Elektrik tüketimi için de benzer gelişmeler gözlemlenmektedir. Uluslararası Enerji Ajansı'nın 2011 tarihli Enerji Raporu'na göre son 25 yıl içinde bütün dünyada elektrik tüketimi çok hızlı bir şekilde artmaktadır, bununla birlikte elektrik tüketiminin diğer son kullanıcı enerji kaynaklarına kıyasla en yüksek artış oranına sahip olması beklenmektedir. Dünya Enerji Konseyi-Türk Milli Komitesi tarafından 2011 yılında yayınlanan raporda, dünya elektrik tüketimi, 2007 yılındaki 18,8 trilyon kilovat-saat seviyesinden 2020 yılında 25 trilyon kilovat-saat değerine ve 2035 yılında ise, 35,2 trilyon kilovat-saat seviyesine ulaşmasının olası olduğu kabul edilmektedir. Ayrıca, OECD ülkelerinde, OECD-dışı ülkelerdeki beklenen %3,3 artışa kıyasla, elektrik tüketimindeki artışının %1,1 olması tahmin edilmektedir. Nihai enerji tüketiminde, elektrik tüketiminin payının 2008 yılındaki %17,3 oranından, 2020 ve 2035 yıllarında sırasıyla, %20 ve %23,5 paylarına artması öngörülmektedir. Türkiye'deki duruma bakıldığında, elektrik tüketimindeki artışın, yüksek ekonomik büyümeyle paralel geliştiği söylenebilir. 1975 ve 2010 yılları arasında elektrik tüketiminin yıllık ortalama %8 oranında arttığı görülmektedir. Toplam elektrik tüketiminde %46 oranıyla en yüksek paya sahip olan sanayi sektörünü, mesken tüketici grubu %24'lük oranla takip etmektedir. Buna mukabil, aynı dönem içinde elektrik üretimi, yıllık ortalama %8 artış oranıyla elektrik tüketimini başa baş takip etmektedir. TEİAŞ tarafından 2012 yılında gerçekleştirilen 10-yıllık kapasite projeksiyon çalışmasıyla, belirsiz kapasite artışları göz ardı edildiğinde ve inşaat halinde olan santrallerin öngörülen tarihlerde işletmeye gireceği varsayımı altında, güvenilir üretim kapasitesinin, yüksek ve düşük talep tahminleri için, sırasıyla, 2017 ve 2019 yıllarında talebi karşılamakta yetersiz olacağı sonucuna ulaşılmıştır. Türkiye'de arz-talep dengesi ile ilgili sorunlar, 1970'lere kadar uzanmaktadır. Elektrik talebini karşılamak için yatırımların yetersiz kaldığı 1973'de ilk kez planlanmış elektrik kesintileri başlamıştır. Aynı sorunların tekrar etmemesi için, yeni kapasite artışlarına yapılan yatırımların hızlanmasının buna ilaveten talep tarafı politikaların da eş anlı uygulanmasının gerekli olduğu görülmektedir. Bu çalışmada, aşağıda gerekçeleri verilmekle birlikte, talep tarafına değinilmektedir. Tezin başlıca amacı, toplam elektrik talebini belirleyen faktörlerin incelenmesi ve özellikle, iktisadi oynaklığın etkisinin belirlenmesidir.

Kirschen (2003) tarafından belirtildiği gibi, elektrik, yüksek yaşam standartlarının, sanayileşmenin, imalatın, ekonomik büyüme ve kalkınmanın sağlanması ve sürdürülmesi için sanayileşmiş toplumlarda vazgeçilmez bir unsurdur. Bu iddia, yukarıda verilen rakamlarla ve elektriğin tarihçesi ile de desteklenmektedir. "1600 yıllarına kadar İngiliz bilim adamı, William Gilbert, elektrik ve manyetizma ile ilgili çalışmalarına başlayana dek, elektrik entelektüel merakın ötesine geçememiştir" (Stewart, 2001: 50) ve elektrik kelimesi, Gilbert'in sürtmeyle küçük maddeleri çekmesi özelliğini ifade etmek için kullandığı Latince "electricus" kelimesi kökeninden gelmektedir (Baigrie, 2006; Chalmers, 1937). Daha sonraları, 1752'de Benjamin Franklin deneyinde aydınlanmanın elektriksel bir olay olduğunu göstermesi (Uman, 1987), elektriğin kullanım alanlarının belirlenmesine yönelik ilk deneysel adım olarak görülebilir. 1821 yılında Michael Faraday tarafından elektrik motorlarının icadı, 1879 yılında Thomas Edison'ın ampulü buluşu ve 19'ncu yüzyılda birçok ilerlemeyle birlikte, elektrik, sanayileşmenin ve modern hayatın vazgeçilmez bir aracı olmuştur. Fakat çoğu elektrik santrali projesinin işletmeye giriş sürecinin uzun sürmesi ve sermaye yoğun yapıya sahip olması nedeniyle, artan tüketimi karşılamak için elektrik üretim kapasitesinin genişletilmesi zor olabilmektedir. Buna ilaveten, elektrik üretiminde fosil yakıtlarının yoğun kullanımının sonucu olarak ortaya çıkan çevresel sorunlara (örneğin, kirlilik, asit yağmurları ve iklim değişikliği) karşı artan çevre bilinci ve ayrıca, arz güvenliğinde belirsizliğe neden olan ve enerji ithalatının yüksek maliyetleri sebebiyle cari açık üzerine aşırı baskıya yol açan enerjide yüksek seviyede dışa bağımlılıkla ilgili politik ve ekonomik endişeler, talep tarafı ile ilgili enerji politikalarının arz tarafı politikalarıyla eş zamanlı uygulanması gerektiğini açığa vurmaktadır. Narayan ve Smyth (2005) ve Carlos vd. (2009) tarafından öne sürüldüğü gibi, gelir ve fiyat esnekliklerinin doğru tahmin edilmesi ve elektrik talebinin anlaşılması, elektrik talebi projeksiyonları, yatırım planlaması, sektörün denetlenmesi ve düzenlenmesi, talep yönetimi ile ilgili politikaların oluşturulması, elektrik sektörünün yeniden yapılanması ve uygulanan politikaların sosyal, ekonomik ve çevresel etkilerinin belirlenmesi açısından önem arz etmektedir. Akademik yazında, Houthakker (1951)'in öncü çalışmasından itibaren elektrik talebinin tahmini birçok araştırmacının ilgisini çekmiştir. Dahl (2011), 1951 ve 2008 yılları arasında 450'den fazla çalışmanın elektrik talep tahmini üzerine yapıldığını belirtmektedir. Çalışmamızda yer alan yazın taramasında sadece, elektrik talebinin esnekliklerinin tahmini üzerine yapılan ekonometrik çalışmalar dikkate alınmıştır. Elektrik talebinin projeksiyonu ile ilgili Rhys (1984), Stoll (1989), Fisher vd. (1992), Toptaş (1992), Şahin (1993), Gellings (1996), Cullen (1999), Mehra ve Bharadwaj (2000) ve Feinberg ve Genethliou (2005) çalışmalarında, yazında ve sektörde kullanılan yöntemlerle ilgili özet bilgiler verilmektedir. Bunun dışında elektrik talebinin esnekliklerinin tahminleri ile ilgili daha önce yapılmış çalışmaların sonuçlarını inceleyen birçok araştırma bulunmaktadır. Bu çalışmalar içinde, en eskisi Taylor (1975) ve Pachauri (1975) tarafından yapılan yazın taramaları olup, Bohi ve Zimmerman (1984), Bates ve Moore (1992), Fisher vd. (1992), Dahl (1993), Madlener (1996), Dahl ve Roman (2004), Kriström (2008), Khanna ve Rao (2009), Yépez-García vd. (2011) ve Heshmati (2012) tarafından yapılan çalışmalarda, elektrik talebini incelerken dikkat edilmesi gereken hususlarla ilgili bilgiler verilmiş, buna ilaveten, eski çalışmaların sonuçları değerlendirilmiştir, karşılaştırılmıştır ve mümkün olduğu durumlarda genel sonuçlar çıkarılmıştır. Bu çalışmaların dışında, Espey ve Espey (2004), konut/mesken sektörünü üzerine olan elektrik talebi çalışmalarında farklılıkların anlaşılması için, meta analizi gerçekleştirmiştir. Modelde, uzun ve kısa dönem fiyat ve gelir esneklikleri, veri özellikleri, model yapısı, tahmin tekniği ve çalışmanın dikkate aldığı zaman periyodu ve bölgenin bir fonksiyonu olarak açıklanmıştır. Elektrik talebi yazınında, Heshmati (2012) tarafından şu hususlara dikkat çekildiği belirtilmiştir: elektrik fiyatlarının içselliği, fonksiyonel form, lineer olmama durumu, verinin çeşidi, spesifikasyon ve tahmin etme yöntemi. Heshmati (2012) her bir hususla ilgili detaylı bilgi vermektedir. Geçmiş yazın araştırmaları ise, bu konuların yanında, verinin toplulaştırılma (aggregation) seviyesi ve fiyat değişkeni için marjinal ya da ortalama fiyat kullanımının seçimi ile ilgili noktalara da değinmişlerdir. Şu ana kadar gerçekleştirilen çalışmalara bakıldığında, birçok çalışma, mesken, ticaret, sanayi ve diğer sektörler gibi sadece bir sektörü analiz ederken, bazı çalışmaların ise bütün sektörler üzerine çalışarak, sektörel esneklikleri karşılaştırdıkları görülmektedir. Bunun dışında, herhangi bir sektör ayrımı yapmadan, toplam (aggregate) elektrik talebini inceleyen çalışmalar da bulunmaktadır. Bu konudaki seçim, çalışmanın amacıyla yakından ilgilidir. Çalışmalarda kullanılan veri çeşidi de farklılık göstermektedir. Şöyle ki, bazı çalışmalar, ulusal seviyede veri kullanırken, bölgesel seviyede veri kullanan çalışmalar da mevcuttur. Analiz için gerekli olan verilerin ve metotların varlığına bağlı olarak, firmalar ya da hane halkları seviyesinde olan mikro veri kullanımı artmaktadır. Veri çeşidi uygulanacak yöntemleri belirlemektedir ama genel olarak, metotlar, zaman serisi metotları ve panel veri metotları olmak üzere ikiye ayırabilmektedir. Bütün bu faktörlerin yanı sıra, incelenen zaman periyodu ve ülkeye göre, çalışmalar farklı sonuçlara ve esneklik tahminlerine ulaşmışlardır. Esneklikler arasında çok fazla farklılıklar olduğu için herhangi bir ortak görüşe ve genel bir sonuca ulaşmak zordur. Fakat Dahl (1993) ve Al-Faris (2002) tarafından da dikkat çekildiği gibi, son 20 yıl içinde modelleme yaklaşımlarında, fonksiyonel formlarda ve ekonometrik tekniklerde çeşitli gelişmeler olmuştur ve bunun da daha güvenilir esneklik tahminlerini sağlaması beklenmektedir.

Bu tez çalışmasında, ampirik uygulamada kullanılan model, iktisat teorisine ve ampirik yazına dayalı olarak oluşturulmuştur. Heshmati (2012) tarafından da belirtildiği üzere, elektrik talep modellerinde, diğer malların talebinde olduğu gibi, gelir ve fiyat başlıca belirleyicilerdir, bunların yanı sıra, verinin toplulaştırılma seviyesine ve mevcut olma durumuna göre, model spesifikasyonuna eklenebilecek değişkenleri, Heshmati (2012), hava durumuyla ilgili ve mevsimsel faktörler, firma ve endüstri özellikleri ve nüfus ve hane halkı kompozisyonu gibi piyasa ve iklim özellikleri ve kısıtlamalar, eğitim ve kampanyalar gibi fiyat-dışı kontrol değişkenleri olarak listelemiştir. Toplam elektrik talebini inceleyen bazı çalışmalar şunlardır: Murray vd. (1978), Reister (1986), Soysal (1986), Pouris (1987), Hsiao vd. (1989), Whittaker ve Barr (1989), Ramcharran (1990), Bates ve Moore (1992), Balabanoff (1994), Diabi (1998), Bakırtaş vd. (2000), Nasr vd. (2000), Lundmark (2001), Al-Faris (2002), Al-Faris (2002), Akan ve Tak (2003), Fatai vd. (2003), Lin (2003), Kamerschen ve Porter (2004), De Vita vd. (2006), Atakhanova ve Howie (2007), Erdoğdu (2007), Amarawickrama ve Hunt (2008), Contreras (2008), Ma vd. (2008), Abosedra vd. (2009), Amusa vd. (2009), Bhargava vd. (2009), Issa ve Bataineh (2009), Khan ve Qayyum (2009), Chaudhry (2010), Inglesi (2010), Jamil ve Ahmad (2010), Lee ve Lee (2010), Sohaili (2010), Alter ve Syed (2011), Bekhet ve Othman (2011), Ekpo vd. (2011), Fan ve Hyndman (2011), Jamil ve Ahmad (2011), Madlener vd. (2011), Yépez-García vd. (2011), Gam ve Rejeb (2012), Maden ve Baykul (2012), Zaman vd. (2012) ve Ziramba ve Kavezeri (2012). Bu çalışmalar içinde, Murray vd. (1978), ekonominin geneli için toplam talep esnekliklerinin oluşturulmasında, tek tek sektörel elektrik talep modeli tahminlerinden elde ettikleri sektörel esnekliklerin ağırlıklı ortalamasını kullanmışlardır, fakat bu şekilde bir yaklaşım Pouris (1987) tarafından eleştirilmiştir. Pouris (1987), Fatai vd. (2003), Amusa vd. (2009), Jamil ve Ahmad (2010), Sohaili (2010), Yépez-García vd. (2011), Ziramba ve Kavezeri (2012) ve Whittaker ve Barr (1989), elektrik talep modellerinde sadece, reel marginal/ortalama elektrik fiyatını ve reel geliri açıklayıcı değişken olarak dikkate almışlardır. Bunlara ek olarak yazında, toplam elektrik talebinin belirleyicileri olarak çeşitli değişkenler kullanılmıştır. Örneğin, elektrik fiyatı ve reel gelir değişkenlerinin yanında, Soysal (1986) tarafından zaman trendi; Erdoğdu (2007), Chaudhry (2010), Inglesi (2010), Lee ve Lee (2010), ve Maden ve Baykul (2012) tarafından nüfus; Al-Faris (2002) tarafından LPG fiyatı; Akan ve Tak (2003) tarafından nüfus ve zaman trendi; Amarawickrama ve Hunt (2008) tarafından nüfus ve temel enerji talep trendi; Issa ve Bataineh (2009) tarafından nüfus ve sanayi enerji etkinliği; Khan ve Qayyum (2009) tarafından müşteri sayısı ve sıcaklık; Alter ve Syed (2011) tarafından elektrikli aletler stoku ve toplam müşteri sayısı; Ekpo vd. (2011) tarafından nüfus ve sanayi üretimi; Diabi (1998) tarafından şehirleşme, elektrikli alet fiyatları ve sıcaklık; Lin (2003) tarafından nüfus, ağır sanayinin oranının düşüşünden kaynaklanan yapısal değişimi kontrol eden bir değişken ve enerji etkinliği gelişimini yansıtan enerji yoğunluğu endeksi; Kamerschen ve Porter (2004) tarafından reel doğal gaz fiyatı, ısıtma ve soğutma gün dereceleri; Atakhanova ve Howie (2007) tarafından nüfus, toplam brüt bölgesel hâsıla içinde sanayinin payı ve sanayi sektöründe etkinlik; Bekhet ve Othman (2011) tarafından gaz fiyatı, şehir nüfusu ve kırsal nüfus; Fan ve Hyndman (2011) tarafından nüfus, ısıtma ve soğutma gün dereceleri; Jamil ve Ahmad (2011) tarafından reel dizel fiyatı, gün dereceleri ve toplam sermaye stoku; Hsiao vd. (1989) tarafından ikame mal fiyatı olarak reel doğal gaz fiyatı, iklim koşullarını temsilen ısıtma ve soğutma gün dereceleri ve bölgesel ve mevsimsel faktörler; De Vita vd. (2006) tarafından hava sıcaklığı, HIV vaka oranı, dizel ve gaz yağının marjinal fiyatı; Contreras (2008) tarafından nüfus, doğal gaz fiyatı, ısıtma ve soğutma gün dereceleri ve bölgesel faktörler; ve son olarak, Bhargava vd. (2009) tarafından maksimum elektrik talebi, mevsimsel yağış miktarı, sıcaklık değişkenliği ve nem değişkenliği gibi hava durumu ile ilgili değişkenler kullanılmıştır. Bakırtaş vd. (2000), uzun dönem elektrik talebi modeline sadece kişi başına geliri eklemişlerdir. Gayrisafi yurtiçi hâsıla için güvenilir veri bulunmadığından ve tayınlama politikasından dolayı, Nasr vd. (2000) elektrik tüketimini toplam ithalat ve gün derecelerinin bir fonksiyonu olarak modellemişler, Abosedra vd. (2009) aynı ülke, Lübnan, için yaptıkları çalışmalarında modellerine önceki açıklayıcı değişkenlerin yanı sıra görece nemliliği de eklemişlerdir. Pakistan için, Zaman vd. (2012), kişi başına elektrik tüketiminin açıklanmasında doğrudan yabancı yatırımları, kişi başına gayrisafi yurtiçi hâsıla ve nüfus artışı gibi açıklayıcı değişkenleri dikkate almışlardır. Ma vd. (2008), Madlener vd. (2011), ve Gam ve Rejeb (2012) gibi bazı çalışmalar, fiyat ve çapraz fiyat esnekliklerinin elde edilmesinde yakıtlar arası ikame modellerini kullanmışlardır.

Elektrik, arz ve talep edilen herhangi bir mal gibi ele alınabilirse de, elektrik talebi üzerine analiz yapılırken, elektriği diğer mallardan ayıran özelliklerini dikkate almak gerekir. Öncelikle, elektrik depolanamadığından dolayı, herhangi bir zamanda talep, yeterli miktarda arz ile karşılanmalıdır. Ayrıca, elektrik talebi türetilmiş taleptir, şöyle ki, elektrik sadece elektrikli aletler, makinalar ve teçhizat aracılığıyla hizmet sağlamaktadır. Diğer bir yandan, birçok ülke, elektrik sektörünün yapısında ve organizasyonunda bir dönüşüm süreci yaşamaktadırlar. Yeniden yapılanma sürecinin ilerlemesiyle, sektör belirsizliğe daha çok maruz kaldığından dolayı, geleneksel planlama yöntemlerinin uygun olmayacağı düşünülmektedir. Bu yüzden, yeni yöntem ve modeller geliştirilmelidir. Bu doktora tezinin amaçları, elektrik talebinin belirleyicilerinin araştırılması ve fiyat ve gelir esnekliklerinin bulunmasıdır ve bunlara ilaveten, ekonomik belirsizliğin/oynaklığın elektrik talebi üzerine etkilerinin incelenmesidir. Bu amaçlarla, toplam elektrik talebi, elektrik fiyatının, gelirin, şehirleşme oranının, hava durumu değişkenlerinin ve iktisadi oynaklığın bir fonksiyonu olarak modellenmiştir. Analizin, sektör bazında ayrıştırma yapılmadan toplu seviyede yapılmasının nedeni, Pouris (1987)'in çalışmasında ifade ettiği gibi, daha istikrarlı bir ilişkinin ve toplam ekonomi için yansız esnekliklerin elde edilebilmesidir. Yüksek iktisadi aktivite, elektriğe kolay erişebilme imkânının ve elektrikli aletlerin elde edilmesinin ve kullanımının artması ve ısınma ve soğutma gereksinimindeki artış, elektrik tüketimini arttıracağından, gelirin, şehirleşmenin ve hava durumu değişkenlerinin elektrik talebi üzerinde pozitif etkisinin olması beklenmektedir. Fakat belirsizlik altında yatırım teorilerine, reel opsiyonlara, üretici teorisine ve normal mallar için tüketici teorisinde talep kanuna dayalı olarak, iktisadi oynaklığın ve elektrik fiyatlarının elektrik talebi üzerine etkilerinin olumsuz olması öngörülmektedir. Enerji çalışmalarının içinde iktisadi oynaklığın etkilerini inceleyen çok fazla çalışma bulunmamaktadır. İktisadi oynaklık, Molls (2000), Radchenko (2005), Kellogg (2010), Görmüş (2012), Pourshahabi vd. (2012), ve Romano ve Scandurra (2012) çalışmaları gibi çok az sayıda enerji çalışmasında modele dâhil edilmiştir. Dinamik kesikli seçim modeli çerçevesinde Molls (2000) batık maliyetlerin ve petrol fiyat oynaklığının petrol üretim faaliyetlerine herhangi bir belirgin etkisinin olup olmadığını araştırmıştır ve sonuçlar, petrol üretim olasılığı üzerine petrol fiyat oynaklığının pozitif ama istatistiksel olarak anlamsız etkisinin olduğunu, buna karşın, batık maliyetlerin önemli bir etmen olduğunu göstermektedir. Radchenko (2005) ise, petrol fiyatları oynaklığının benzin fiyatlarındaki asimetri üzerine etkisini incelemiş ve ikisi arasında negatif bir ilişki bulmuştur. Kellogg (2010), örtük petrol fiyatları oynaklığının petrol kuyularına yapılan yatırıma etkisini araştırmak amacıyla, firmaların sondaj yatırımlarını zamanlama problemi için dinamik model geliştirmiş ve örtük petrol fiyatları oynaklığı yüksek olduğunda firmaların sondaj aktivitelerini azalttığı sonucuna ulaşmıştır. Diğer bir çalışma Görmüş (2012) tarafından gerçekleştirilmiştir ve hisse senetleri piyasası oynaklığının enerji şirketlerinin hisse senetlerinin getirileri üzerine etkileri incelenmiştir. Güneş enerjisi şirketlerinin hisse senetleri dışındaki şirketlerin hisse senetleri için belirgin bir ilişki bulunamamıştır. Romano ve Scandurra (2012) petrol fiyatlarındaki oynaklığın ve Platt fiyat oynaklığının sırasıyla sanayi benzin fiyatındaki ve perakende benzin fiyatındaki asimetri üzerine etkilerini analiz etmişler ve yüksek fiyat oynaklığıyla birlikte asimetri derecesinin azaldığını bulmuşlardır. Belirsizliği dikkate alan diğer bir enerji çalışması, Pourshahabi vd. (2012) tarafından EGARCH modelinden elde edilen petrol fiyatları oynaklığının petrol tüketimi modeline dâhil edilmesiyle gerçekleştirilmiştir. OECD ülkeleri için 1980 ve 2008 yıllarını dikkate alan ve panel veri yöntemlerini uyguladıkları analizlerinden petrol fiyat oynaklığının OECD ülkelerinde petrol tüketimi üzerine belirgin ve olumsuz etkilerinin olduğunu bulmuşlardır. Bilgimiz dâhilinde, akademik yazında, iktisadi oynaklığın elektrik talebi modellerine dâhil edildiği bir çalışma yer almadığı görülmüştür. Oysaki belirsizlik altında yatırım teorileri ve reel opsiyonlara dayalı olarak, Robays (2012)'e göre, belirsizlik üretim ve tüketim kararlarında ertelemelere yol açmakta, dolayısıyla, iktisadi ajanların kararlarını etkilemektedir. Elektrik talebi de iktisadi bir karar olduğu için, iktisadi oynaklığın elektrik talebi üzerine belirgin etkilerinin olması beklenir. Elektrik talep modellemelerinde dikkat gerektiren diğer önemli bir husus, ekonomik faktörlerin kısa ve uzun dönem etkilerinin ayrıştırılması gerekliliğidir. Bunun nedeni, sürtünmeler, alışkanlık oluşumu, atalet, var olan sermaye stokunun yenilenmesi ve yeni kapasite eklenmesinin neden olduğu uyum maliyetleri, fiyat beklentileri ve bilgi eksikliği dolayısıyla, elektrik talebinin herhangi bir belirleyicisinde oluşan şok sonucunda denge seviyesine ulaşmasının hemen gerçekleşememesidir. Kısa dönemde, diğer sabit üretim faktörleri gibi, elektrikli alet, makine ve teçhizat stokları da sabit olduğu için, elektrik talebini sadece, sabit elektrikli teçhizat stokunun kullanım oranını değiştiren faktörler belirlemektedir. Buna karşın, uzun dönemde, ekonomik faktörlerdeki değişme sonucunda elektrikli alet, makine ve teçhizatın etkinliği ve stok miktarı değişebilir. Ayrıca, "üreticiler, çoğunlukla beklenen fiyatlara göre kararlarını aldıkları için görece fiyat değişikliklerine tepkileri hemen gerçekleşmemektedir" (Considine ve Mount, 1984: 438). Bu yüzden, ekonomik faktörlerin birindeki bir değişimden hemen sonra, talep uzun dönemdeki dengesine ulaşamamaktadır. "Bu durum, uzun ve kısa dönemin açık bir şekilde dikkate alındığı dinamik modellerin kullanımını gerektirmektedir" (Olsen ve Roland, 1988: 16).

Daha önceki çalışmalarda elde edilen gelir ve fiyat esnekliklerinin tahminlerini incelediğimizde, akademik yazının elektrik talebinin fiyat ve gelir esnekliği ile ilgili bir mutabakata ulaşamadığı görülmektedir. Toplam elektrik talebi ile ilgili yapılan çalışmalar, dinamik modellerden elde edilen elektrik talebinin kısa ve uzun dönem gelir (fiyat) esnekliklerinin sırasıyla, 0.02 ve 2.24 (-0.03 ve -1.67) ve 0.203 ve 5.39 (-0.003 ve -6.849) aralıklarında olduğunu göstermektedir; bunun dışında statik modellere dayalı çalışmalar, gelir ve fiyat esnekliklerini, herhangi bir kısa ve uzun dönem ayrımı yapmadan, (0.19 ve 0.89) ve (-0.09 ve -0.73) aralıklarında bulmuşlardır. Fakat kısa dönemde elektrikli aletlerin, makinaların ve teçhizatın stoklarının sabit olmasından dolayı sadece bu sabit stokun kullanım oranını değiştiren faktörler elektrik talebini etkileyebilir; buna karşın, uzun dönemde, elektrikli aletlerin, makinaların ve teçhizatın stokunun ve etkinliğinin ekonomik faktörlerdeki değişikliklere bağlı olarak değişken olabilmesi nedeniyle, uzun dönem esnekliklerinin kısa dönem esnekliklere kıyasla daha yüksek olması beklenir. Şu ana kadarki yapılan açıklamalar, teori ve geçmiş ampirik yazın dikkate alınarak, çalışmada aşağıdaki hipotezler test edilmiştir;

Hipotez 1: Uzun dönemde, elektrik talebi kısa döneme kıyasla gelir ve fiyat değişimlerine daha duyarlıdır, bu açıdan, fiyatlama politikaları uzun dönemde daha etkin olabilmektedir.

Hipotez 2: Şehirleşme elektrik talebini belirgin bir şekilde arttırmaktadır.

Hipotez 3: Isıtma ve soğutma gereksinimleri elektrik talebini belirgin bir şekilde arttırmaktadır.

Hipotez 4: İktisadi volatilite elektrik talebini belirgin bir şekilde azaltmaktadır.

Hipotez 5: Elektrik tüketimiyle gelir arasında çift yönlü nedensellik ilişkisi bulunmaktadır, şöyle ki, yüksek gelir seviyesi elektrik tüketimini arttırırken, yüksek elektrik tüketimi gelir seviyesinde artışa neden olmaktadır. (Geri besleme hipotezi).

Bu doktora çalışması, iki tane panel veri uygulaması içermektedir: biri, 1990'dan 2001'e kadarki dönemi kapsayan Türkiye'nin illeri üzerinedir; diğeri ise, 1985 ve 2007 yılları arasındaki dönem içinde 27 OECD ülkesinin panel verisi uygulamasıdır. Bu çalışmada, elektrik talebindeki dinamikleri, eğilimleri ve yatay kesitler arası farklılıkları eşanlı olarak dikkate almak için çeşitli panel veri teknikleri kullanılmıştır. Bu teknikler içinde en önemlileri, dinamik panel veri modelinin tahmininde kullanılan Arellano ve Bond (1991) Genelleştirilmiş Momentler Metodu (GMM) ve Blundell ve Bond (1998) sistem GMM teknikleri, birinci ve ikinci kuşak panel birim kök testleri (Levin, Lin ve Chu (2002), Breitung (2000), Im, Pesaran ve Shin (2003), Maddala ve Wu (1997), Choi (2001), Hadri (2000), Pesaran (2007) ve Carrion-i-Silvestre vd. (2005)), birinci ve ikinci kuşak panel eş bütünleşme testleri (Pedroni (1999, 2004), Kao (1999), Larsson, Lyhagen ve Löthgren (2001), Westerlund (2006) ve Westerlund (2007)), panel kendisiyle bağlaşımlı dağıtılmış gecikme (ARDL) modelinin tahmininde kullanılan Pesaran vd. (1999)'nin ortalama grup (MGE) ve havuzlanmış ortalama grup tahmincileri (PMGE), panel hata düzeltme modelinin tahmininde kullanılan Pesaran (2006) tarafından geliştirilen ortak ilişkili etkiler- (CCE-) MGE ve havuzlanmış (CCEP) tahmincileri ve panel vektör hata düzeltme yöntemleriyle gerçekleştirilen panel Granger nedensellik testleri olarak sayılabilir. Bunların dışında eş bütünleşme ilişkisinin tahmininde de Pedroni (1996,2000) ve Phillips and Moon (1999)'nun geliştirdiği

Düzenlenmiş/Geliştirilmiş En Küçük Kareler (FMOLS) grup tahmincisi; Mark and Sul (2003) tarafından bulunan panel dinamik En Küçük Kareler (PDOLS) yöntemi; Pesaran vd. (1999) ve Pesaran ve Smith (1995) tarafından tasarlanan MGE tahmincisi; Breitung (2005)'un panel iki aşamalı tahmincisi; Bai and Kao (2006) tarafından geliştirilen sürekli güncelleştirilen Düzenlenmiş/Geliştirilmiş tahminci; Pesaran (2006)'nın ortak ilişkili etkiler- (CCE-) MGE ve havuzlanmış tahmincileri kullanılmış ve sonuçlar karşılaştırılmıştır. "Enerji talep modellemesinde Griffin (1993), 1970'den itibaren üç başlıca gelişmeden bahsetmiştir" (Bhattacharyya ve Timilsina, 2009: 30). Bu gelişmelerden bir tanesi panel veri metodudur. "Zaman serisi verilerinde dikkate alınan kısa dönem uyarlanma sürecinin aksine, panel veri analizi, bölgelerarası farklılıkların dikkate alınmasını sağlayarak uzun dönem uyarlanma sürecini yansıtabileceği düşünülebilmektedir" (Bhattacharyya ve Timilsina, 2009: 30). İktisadi oynaklık, geçmiş verilere (genelleştirilmiş) otoregresif koşullu değişen varyans (ARCH/GARCH) modelleri uygulanarak elde edilmiştir. "Engle (1982)'in enflasyon belirsizliği üzerine gerçekleştirdiği özgün çalışmasından itibaren ARCH modelleri belirsizliğin ölçülmesinde yaygın olarak kullanılmaktadır" (Elder ve Serletis, 2010: 1140). Sonuçların, ekonomik oynaklığın ölçülmesinde kullanılan farklı temsili değişkenlere karşı istikrarını kontrol etmek için, Türkiye'nin illeri üzerine yapılan panel veri uygulamasında, döviz kuru oynaklığı, sanayi üretimi oynaklığı, hisse senetleri piyasası oynaklığı ve petrol fiyatları oynaklığı dikkate alınmıştır.

Ampirik analiz sonuçları, modellere dinamik yapının eklenmesinin ve panel ve zaman serilerinin birim kök özelliklerinin dikkate alınmasının önemini vurgulamaktadır. Türkiye için yapılan panel veri uygulamasında, dinamik panel veri modelinin sistem GMM tahmini sonucu elde edilen esneklik tahminleri, farklı oynaklık değişkenleri kullanarak yapılan tahminlerde tutarlılık göstermekte olup, sadece sanayi üretimi ile ilgili belirsizliğin istatistiksel olarak belirgin ve pozitif bir etkisinin olduğu bulunmuştur ve bu pozitif etki ihtiyatlı tasarruf güdüsü ve Black (1987)'in iddiası ile açıklanabilir. İhtiyatlı tasarruf güdüsüne göre, artan belirsizlik tüketimde azalmaya, tasarruflarda artışa neden olmakta ve dolayısıyla yatırımlar artmaktadır. Yatırımlardaki artış ekonomik büyümeyi hızlandırdığından dolayı, ekonomik büyüme etkisinin tüketimi azaltma etkisinden çok daha fazla olacağı varsayımı altında, elektrik tüketimine artan belirsizliğin net etkisinin artırıcı yönde olması beklenmektedir. Black (1987) tarafından da ayrıca, büyüme belirsizliğinin büyümeyi arttırdığı iddia edilmektedir. Diğer taraftan, belirsizlik altında yatırım teorilerine ve reel opsiyonlar etkisine bağlı olarak, belirsizlik yatırım, üretim ve tüketimde gecikmelere yol açmakta ve bu yüzden, elektrik tüketiminde azalma beklenmektedir. Bir çok ampirik ve teorik çalışma, belirsizliğin ekonomik aktiviteler ve kararlar üzerinde olumsuz etkisi olduğunu belirtmekteyse de belirsizliğin pozitif etkileri olduğunu gösteren bazı istisnai çalışmalar da bulunmaktadır. Örneğin, Grier ve Tullock (1989), Caporale ve McKiernan (1998), Kormendi ve Meguire (1985), Grier ve Tullock (1989) çalışmaları, ekonomik büyümenin, büyüme oynaklığından olumlu yönde etkilendiğini bulmuşlardır. Diğer bir örnek olarak ise, petrol fiyatlarının oynaklığındaki artışın yatırım ve reel gayrisafi yurtiçi hâsıla üzerine artıcı etkilerinin olduğunu gösteren Plante ve Traum (2012)'un çalışması gösterilebilir. Son olarak, Molls (2000) petrol üretimi olasılığı üzerine petrol fiyatları oynaklığının etkisinin pozitif ama istatistiksel olarak anlamsız olduğunu bulmuştur. Bunun dışında sonuçlar, Türkiye için gelir esnekliğini 0.35 ve 0.43 arasında olduğunu göstermektedir. Fiyat esnekliği ise -0.11 ve -0.59 arasında bulunmuştur. Hem fiyat hem de gelir esneklikleri, teorik olarak geçerli işaretlere sahip olup, daha önceki çalışmaların esneklik tahminleri aralığında yer almaktadır. Bu esneklik tahminlerinden, elektrik talebinin gelire ve fiyata göre esnek olmadığı sonucuna ulaşılabilir. Sonuçlarımız, kısmi uyarlama modelini kullanan, panel ve zaman serilerine dayalı daha önceki çalışmalar tarafından da desteklenmektedir. Örneğin, Hsiao v.d. (1989), Diabi (1998) ve Bhargava v.d. (2009) tarafından da elektrik talebinin gelire ve fiyata karşı esnek olmadığı bulunmuştur. Bu sonuçlara ek olarak, analizimizde şehirleşme oranının ve sanayi üretimi oynaklığının elektrik talebini belirgin ve pozitif etkilediği gözlemlenmektedir.

OECD ülkeleri için yapılan panel veri çalışmasında dinamik model sonuçlarına bakıldığında, eğim katsayılarının ülkeler arasındaki homojenliği varsayımına bağlı olarak sonuçların farklılaştığı gözlemlenmektedir. Bu modeller arasında sistem GMM tekniğiyle tahmin edilen dinamik panel veri modeli eğim katsayılarının ve hata teriminin varyansının homojen olduğu varsayılmaktadır. PMGE ile tahmin edilen ARDL modeline dayalı hata düzeltme modeli ile CCE-MG tahminine dayalı hata düzeltme modelinde uzun dönem katsayıların homojenliğini varsayılmakta ama sabit katsayılarının, kısa dönem eğim katsayılarının ve kısa dönem hata terimi varyanslarının ülkeler arası farklılaşmasına izin verilmektedir. Dinamik panel veri modelinin tahmin sonuçlarında, bütün katsayılar teorik açıdan uygun işaretlere sahip olup, petrol fiyatları oynaklığı dışında bütün değişkenlerin katsayıları istatistiksel olarak anlamlıdır. Murray vd. (1978), Diabi (1998), ve Erdoğdu (2007) çalışmalarının sonuçlarıyla paralel olarak elektrik talebinin gelire ve fiyata göre esnek olmadığı sonucuna ulaşılmıştır. Gelir (fiyat) esneklikleri, 0.094 (-0.076) olarak bulunmuştur ve daha önceki çalışmalardan elde edilen esnekliklerin aralığında yer almaktadır. PMGE ile tahmin edilen ARDL modeline dayalı hata düzeltme modelinden de biraz farklılıklarla birlikte dinamik panel model sonuçlarına benzer sonuçlar elde edilmiştir. Uzun dönemde petrol fiyatları oynaklığı dışında bütün etmenlerin belirgin etkileri olduğu, buna karşın, kısa dönemde, sadece petrol fiyatları oynaklığı ve bir dönem gecikmeli gelir değişkenlerinin etkileri anlamlı bulunmuştur. Sonucumuz, Bredin vd. (2008) tarafından öne sürülen petrol fiyatlarında artış ve azalışların kısa dönem daraltıcı etkilerinin olduğu iddiasını destekler niteliktedir. Weiner (2005) de ayrıca, petrol fiyatları oynaklığının yatırım ve istihdam üzerine olumsuz etkilerinin olduğunu belirtmiştir. Kısa ve uzun dönem gelir (fiyat) esneklikleri, 0.070 ve 0.324 (0.050 ve -0.116) olarak tahmin edilmiştir ve esneklik tahminleri geçmiş çalışmalarından elde edilen tahminlerle paralellik göstermektedir. Fakat, kısa dönem esneklikler istatistiksel olarak anlamlı bulunmamıştır. Kısa dönem pozitif fiyat esnekliği bazı ülkelerde Bhargava v.d. (2009) tarafından belirtildiği gibi devlet tarafından bazı nihai elektrik tüketici gruplarına sağlanan yüksek sübvansiyonların bir göstergesi olabilir. İstatistiksel olarak anlamlı ve negatif işaretli hata düzeltme terimi, 0.559'luk uyarlanma hızıyla dengeye yakınsandığını işaret etmekte, bu ise, herhangi bir şoktan sonra, bir sene içinde elektrik tüketiminin uzun dönem denge seviyesinden sapmaların %55.9'luk oranının düzeltildiğini göstermektedir. Uzun ve kısa dönem elektrik talebinin, gelire ve fiyata göre esnek olmadığı, fakat uzun dönemde talebin gelirdeki ve fiyattaki değişimlere daha duyarlı olduğu bulunmuştur. Uzun dönem esnekliklerin kısa döneme göre daha büyük olması, teorik bir gereklilik olup, bu sonuç daha önce yapılan bir çok ampirik çalışmada da vurgulanmıştır. Carlos vd. (2009) bu bulguyu, otoprodüktör faaliyetlerin sanayi sektöründe özellikle son dönemlerde artmasının ve hem konutlarda hem de sanayide eski elektrikli aletlerin, makinelerin ve teçhizatın daha enerji etkin olanlarıyla değiştirilmesinin bir sonucu olarak açıklamışlardır. Sonuçlarımız, eş bütünleşme modeli, (vektör) hata düzeltme modeli, kendisiyle bağlaşımlı dağıtılmış gecikme modeli gibi çeşitli dinamik modeller kullanan, panel ve zaman serilerine dayalı daha önceki çalışmalar tarafından da desteklenmektedir. Lundmark (2001), Oman için Al-Faris (2002), Lin (2003), De Vita vd. (2006), Inglesi (2010), Sohaili (2010), Alter ve Syed (2011), Bekhet ve Othman (2011), Ekpo vd. (2011), ve Zaman vd. (2012) gibi çalışmalar da benzer bir sonuca ulaşmışlardır. Hata düzeltme modelinin, CCE-MG tahminine göre, hem uzun hem de kısa dönemde sadece gelir elektrik talebini belirgin bir şekilde belirlemektedir, bununla birlikte petrol fiyatları oynaklığının göz ardı edilebilir etkisinin olduğu bulunmuştur. Uzun ve kısa dönem gelir esnekliğinin birden küçük olması, elektrik talebinin gelir değişikliklerine esnek olmadığını göstermektedir. Türkiye ve OECD ülkeleri için yapılan birçok tahminde, elektrik talebinin düşük gelir esnekliğine sahip olması, Atakhanova ve Howie (2007) ve Yépez-García vd. (2011) tarafından da dikkat çekildiği gibi, ekonominin yapısal kompozisyonunun ya da gayrisafi yurtiçi hasılada yüzde artış için düşük seviyede enerji gereksiniminin işareti olan düşük enerji yoğunluğunun yansıması olabilmektedir.

Genel olarak sonuçları değerlendirmek gerekirse, sonuçlar, OECD ülkeleri için, elektrik tüketimi üzerine petrol fiyatları oynaklığının istatistiksel olarak belirgin kısa dönem olumsuz etkisinin olduğunu göstermektedir. Sonucumuz, Bloom (2009)'un bulgusuyla da paralellik arz etmektedir. Belirsizlik şoklarının etkisini belirlemek amacıyla, Bloom (2009) teorik bir model geliştirmiş ve modelin simülasyonundan, artan oynaklığın kısa dönemde ekonomik aktivitede hızlı ama geçici bir yavaşlamaya yol açtığını, fakat, bu yavaşlamadan sonra ekonominin düzelerek yavaşlama öncesi başlangıç seviyesine ulaştığını gözlemlemiştir. Bu çerçevede, ekonomik şokların asimetrik etkilerinin, kalıcı simetrik etkilerinin tam tersine, geçici olduğunu iddia etmektedir. Bloom (2009), belirsizliğin kısa dönem negatif etkilerinin, kısa dönemde sermaye stokunun sabit olmasının bir sonucu olduğunu, fakat uzun dönemde sermaye stoku değişken olduğu için, kısa dönem etkilerinin uzun dönemde gözlenmediğini ifade etmektedir. Kısa dönemde de olsa oynaklığın elektrik tüketimi üzerine negatif etkisi olduğu bulunmuştur. Bu etkinin azaltılması için eğer mümkünse, oynaklığın azaltılması gerekir ama bunun için oynaklığa neden olan faktörler belirlenmelidir. Bunun dışında bazı oynaklıklar dışsal olduğundan dolayı kaçınılmaz olduğu söylenebilir. Örneğin, petrol fiyatlarının oynaklığının bazı nedenleri, petrol üreten ülkelerdeki politik ve iktisadi istikrarsızlık ve doğal felaketlerdir. Eğer bir ülke (örneğin, Amerika, Japonya, Belçika, İtalya, Almanya, Fransa ve Türkiye gibi) ekonomik aktivitelerinde yoğun bir şekilde ithal petrole bağımlı ise, petrol fiyatlarındaki belirsizliğin olumsuz etkileri kaçınılmaz ve çok maliyetli olabilmektedir. Bu durumda olan bir ülke, dışa bağımlılığını azaltmak için, eğer mümkünse, kendi petrol rezervlerini araştırmalıdır, ya da, petrolü ikame edebilmek için, enerji kaynakları çeşitlendirilmesine ağırlık verebilir. Weiner (2005) ve Pourshahabi vd. (2012) tarafından da önerildiği gibi, petrol ihraç eden ülkeler arasında çeşitlendirme, stratejik petrol rezervleri bulundurma ve vadeli işlem sözleşmeleri ile riskten korunma gibi yöntemler, petrol fiyatları volatilitesinin etkisini azaltmak için diğer çözüm önerileri olarak sıralanabilir. Uzun vadede ülkenin sanayi sektörünü az-enerji yoğun yapıya doğru yeniden yapılandırma alternatif bir çözüm olarak eklenebilir. Bunlara ek olarak, enerji etkinliği ve tasarrufu uygulamalarının yaygınlaştırılmasıyla birlikte, enerji harcamalarının toplam harcamalar içindeki payı azalacağından dolayı, dışa bağımlılığın ve petrol fiyatlarındaki belirsizliğin etkilerinin azalması beklenmektedir. Chen ve Hsu (2012), enerji etkinliğinin petrol fiyatlarındaki oynaklığın uluslararası ticaret üzerindeki olumsuz etkilerinin azaltılmasında etkin olmayan bir araç olduğunu iddia etmesine rağmen, örneğin, Cologni ve Manera (2009) enerji etkinliği ile ilgili gelişmelerin ve mali ve parasal otoritelerce dış kaynaklı arz ve talep şoklarının daha iyi yönetiminin petrol fiyatları oynaklığının ekonomik büyüme üzerine olan etkilerini zaman içinde azalttığını göstermişlerdir. Bunların dışında, gelecekte elektrikli arabaların yaygınlaşmasıyla birlikte, ulaşımda petrol bağımlılığında azalmanın olması beklenmektedir. Rafiq vd. (2009) tarafından, istihdam, büyüme ve yatırım üzerine petrol fiyatlarındaki oynaklığın negatif etkilerinin azaltılması için yurtiçi petrol fiyatlarının sübvansiyonla daha istikrarlı hale getirilmesi önerildiyse de, fiyatlar üzerine direkt yapılan sübvansiyon fiyatlarda çarpıklıklara neden olabileceğinden ve ayrıca devlet bütçesi üzerine ağır bir yük unsuru oluşturacağından dolayı, politika önerileri oluşturulurken, çok yönlü düşünmenin gerekliliğini göstermektedir.

Diğer taraftan, Weiner (2005), petrol fiyatlarındaki oynaklığın, aşağı yönlü fiyat hareketlerinin yanında, ani fiyat artışlarını yönetebilmenin zorluğundan dolayı petrol ihraç eden ülkeler açısından da olumsuz sonuçlar doğurabileceğinden bahsetmektedir. Artan petrol fiyatları belirsizliğinden dolayı, üreticilerin ve endüstriyel tüketicilerin riske maruz kalmasının bir sonucu olarak, Pindyck (2004)'e ve Pourshahabi vd. (2012)'e göre, petrol üreticilerinin yatırım kararları ve doğal gaz ve petrol sektörlerindeki fiziksel sermaye yatırım kararları etkilenebilmektedir. Kellogg (2010) da petrol fiyatlarındaki belirsizlik yüksek olduğunda firmaların petrol arama faaliyetlerini azalttığını bulmuştur.

Analizimizin diğer önemli bir sonucu ise, elektrik talebinin fiyata ve gelire göre uzun ve kısa dönemde esnek olmayışıdır, buna ilaveten büyük çoğunlukla esnekliklerin işaretleri iktisat teorisine uygunluk göstermektedir. Bu sonuç, elektriğin normal mal olduğunu ve bir gereklilik olduğuna işaret etmektedir. Ayrıca, ekonomik faktörlerdeki değişimlere karşı sermaye stokunun uyumlanma sürecinin zaman alması nedeniyle, elektrik talebinin uzun dönemde kısa döneme kıyasla fiyattaki ve gelirdeki değişimlere daha duyarlı olduğu bulunmuştur. Elektrik talebinin esnek olmayışı, "elektriğin üretimde vazgeçilmez olmasından ve sanayileşmiş toplumlarda, birçok birey tarafından belli bir yaşam standardı seviyesinin devamı için olmazsa olmaz olarak görülmesinden" (Kirschen, 2003: 521) kaynaklanmaktadır. Bunun dışında, Kirschen (2003) tarafından da belirtildiği gibi, elektrik maliyeti firmaların toplam maliyetinin ve hane halkının bütçesinin çok cüzi bir oranına tekabül etmektedir. Dahası, Kirschen (2003), daha etkin ve rekabetçi elektrik piyasalarının oluşturulması, fiyatların ani artışlarının azaltılması ve enerji arz güvenliğinin sağlanması amacıyla kısa dönem fiyat esnekliğinin arttırılması yönünde elektrik sektöründe talep tarafının daha aktif katılımını teşvik edecek bazı araçlar önermiştir. Yukarıdaki sonuçlara ek olarak, uzun ve kısa dönem gelir esneklikleri fiyat esnekliklerinden daha büyük bulunmuştur, bu sonuç, Jamil ve Ahmad (2011), Erdoğdu (2007), ve Akan ve Tak (2003) çalışmalarının bulguları tarafından da desteklenmektedir. Esnekliklerle ilgili buraya kadar bahsedilen bulguların önemli politika çıkarımları mevcuttur. Elektrik talebinin fiyat değişimlerine çok duyarlı olmaması, sadece çok yüksek elektrik fiyatı artışlarının istenilen talep azalmalarını sağlayabileceğini göstermekte olup, böyle bir enerji politikasının ise her bir vatandaşa ucuz ve yüksek kalitede elektrik servisini sağlamakla ilgili sosyal politikalara ters düşeceği açıktır. Bu açıdan, sadece elektrik fiyatlarına dayalı politikaların, özellikle kısa dönemde, elektrik talebini azaltmakta çok etkin olabileceği söylenemez. Oysaki uzun dönemde elektrik talebi daha duyarlı olduğu için, kısa döneme kıyasla, fiyat politikalarının daha etkin olabileceği görülmektedir. Bunun yanında, fiyat esnekliğinin birden küçük olmasından dolayı, elektrik fiyatlarında çok az bir artış, üretim, dağıtım, iletim, perakende ve toptan satış şirketlerine yüksek gelir artışı sağlayacaktır. Fakat tüketicilerin istismarının engellenmesi için, iletim, dağıtım ve perakende satış tarifeleri denetlemeye tabidir, ayrıca, üretim, perakende satış ve toptan satış kısımları rekabete açılmıştır. Çok zamanlı tarife, dinamik fiyatlama ve kesilebilir tedarike uygulanan tarife yapısı gibi fiyatlama politikalarının yanında, Bhargava vd. (2009), Narayan ve Smyth (2009), Sa'ad (2009), Jamil ve Ahmad (2010) ve Jamil ve Ahmad (2011) gibi çalışmaların politika tavsiyelerine takiben, arz güvenliğini sağlamak ve ayrıca, çevresel standartları da karşılamak amacıyla elektrik sektöründe arz ve talep taraflarına uygulanabilecek bazı politikalar şu şekilde sayılabilir: bütün sektörleri kapsayacak şekilde enerji etkinliğinin geliştirilmesine yönelik bilgi kampanyalarının ve düzenlemelerin uygulanması; aletler ve makinalar için zorunlu enerji etkinliği standartlarının oluşturulması; bütün bölgeler ve tüketici grupları arasında çapraz sübvansiyonların kaldırılarak tarife yapısının rasyonelleştirilmesi; enerji israfına karşı tüketici bilincini arttıracak kampanya ve eğitimlerin verilmesi; elektrik üretiminde kaynakların çeşitlendirilmesi; yenilenebilir enerji kaynaklarının kullanımının arttırılması; üretim kapasitesinin genişletilmesi; iletim ve dağıtım ağlarına yatırımların yapılması; dağıtımda ve iletimde enerji kayıp ve kaçaklarını azaltacak ve buna ilaveten, elektrik üretiminde etkinlik artışını teşvik edecek çeşitli politikaların, düzenlemelerin ve teknolojilerin uygulanması; bölgelerarası elektrik ticaretinin arttırılması; etkin otoprodüktör üretiminin teşvik edilmesi; sektörde rekabeti ve özel sektör katılımını teşvik edecek politikaların uygulanması; elektrik sektöründe yerli ve yabancı yatırımcılar için kredibiliteyi sağlayacak yasal çerçevenin oluşturulması. Ek olarak, enerji etkinliği programlarını destekleyici yönde bir çalışma olan Berry (2008), Amerika'da yoğun enerji etkinliği programlarının uygulandığı eyaletlerle etkinlik üzerine herhangi bir politikanın uygulanmadığı eyaletlerin karşılaştırılmasına dayanan analizinde enerji etkinliği programlarının elektrik satış miktarını %60 gibi bir oranda azaltarak gayet etkili olduklarını göstermiştir.

Uygun enerji politikaları oluştururken, çalışmamızın dikkat gerektiren son bulgusu, OECD ülkeleri için, elektrik tüketimi ve gelir arasında çift yönlü uzun ve kısa dönem nedenselliğin bulunmasıdır, şöyle ki, iki değişken arasında eş anlı bir ilişki olup, yüksek gelir yüksek elektrik tüketimine neden olurken, tam tersi yönde ilişki de söz konusudur. Elektrik tüketiminin azaltılmasına yönelik politikaları uygulamadan önce, bu politikaların ekonomik büyüme üzerine olası olumsuz etkileri, elektrik tüketiminin gelir esnekliğiyle gelirin elektrik tüketimi esnekliği karşılaştırılarak değerlendirilmelidir. Ancak, bazı enerji politikaları, üretim kapasitesinin genişletilmesi ve enerji verimliliği uygulamaları gibi, elektrik tüketimiyle gelir arasında bu şekilde bir ikileme yol açmamaktadır. Dobnik (2011)'e göre, enerji verimliliği ilerlemelerine dayalı enerji tasarrufu tam aksine, verimlilik artışı aracılığıyla ekonomik büyümeyi sağlamaktadır. Çevresel politikalarla daha uyumlu bir üretim kapasitesi artışını sağlayabilmek için, planlanan kapasitesi artırımında yenilenebilir enerji ve temiz kömür enerji üretim teknolojileri gibi çevre dostu temiz elektrik üretim teknolojilerine daha yüksek oranda pay ayrılabilir. Çift yönlü nedenselliğin diğer önemli bir sonucu, gelirin içselliğini dikkate almayan tek denklemli modellerin elektrik tüketimi projeksiyonlarında kullanılması sonucunda yanıltıcı sonuçlar verme ihtimalinin yüksek olmasıdır. Bu sorun, aracı değişkenler ya da geri besleme etkilerini dâhil eden denklem sistemleri kullanılarak çözülebilir.

Bu çalışmada bazı sınırlamalar olmasına rağmen, çalışma sonuçları, projeksiyon amacıyla, üretim ve iletim yatırım planlamalarında, elektrik üretiminin çevresel etkilerinin değerlendirilmesinde ve enerji politikalarının tasarımında kullanılabilir. Elektrik talebi hem özellikleri açısından hem de gelişim süreçleri itibariyle sektörler arası ve sektör içinde farklılaştığından dolayı, firma ya da hane halkları seviyesinde yapılacak bir analizin, politika yapıcılarına, elektrik kuruluşlarına, nihai kullanıcılara, düzenleyicilere ve elektrik sektöründe yer alan bütün diğer ajanlara daha kapsamlı ve doğru bilgi sağlaması mümkün olabileceğinden, bunları dikkate alan bir çalışmanın yapılması büyük önem arz etmektedir. Gelecekte yapılacak çalışmalar için başka bir öneri ise, Paul vd. (2009)'in de belirttiği gibi, düzenlemelerin, politikaların ve programların elektrik tüketimi üzerine olan etkilerinin dikkate alınmasıdır. Ayrıca, farklı oynaklık değişkenlerinin kullanılması ilginç sonuçlar verebilir.

Appendix 7. Tez Fotokopisi İzin Formu

ENSTİTÜ

Fen Bilimleri Enstitüsü	
Sosyal Bilimler Enstitüsü	X
Uygulamalı Matematik Enstitüsü	
Enformatik Enstitüsü	
Deniz Bilimleri Enstitüsü	

YAZARIN

Soyadı : Akarsu
Adı : Gülsüm
Bölümü : İktisat

TEZİN ADI (İngilizce) : Empirical Analysis of The Relationship Between Electricity Demand and Economic Uncertainty

TEZİN TÜRÜ : Yüksek Lisans [ ] Doktora [X]

1. Tezimin tamamından kaynak gösterilmek şartıyla fotokopi alınabilir. [ ]
2. Tezimin içindekiler sayfası, özet, indeks sayfalarından ve/veya bir bölümünden kaynak gösterilmek şartıyla fotokopi alınabilir. [ ]
3. Tezimden bir (1) yıl süreyle fotokopi alınamaz. [X]

TEZİN KÜTÜPHANEYE TESLİM TARİHİ: