TESTING FOR RATIONAL BUBBLES IN THE TURKISH STOCK MARKET

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ABSTRACT

TESTING FOR RATIONAL BUBBLES IN THE TURKISH STOCK MARKET

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In this thesis we empirically examine whether the Turkish stock market is driven by rational bubbles over the period between March 1990 and February 2012. The bubble periods are estimated using a recently developed right-tailed unit root test, the generalized sup augmented Dickey-Fuller test of Phillips, Shi and Yu (2011a). Applying their bubble detection and location strategies to weekly price dividend ratio series, we find strong evidence for the existence of rational bubbles in the Turkish stock market benchmark indices as well as sector indices. Our located bubble periods may give early warning signals of the subsequent Turkish financial crisis.

Keywords: Rational bubbles, right-tailed unit root test, generalized sup augmented Dickey-Fuller test, price dividend ratio, early warning signals

ÖZ

TÜRK HİSSE SENEDİ PİYASASINDAKİ RASYONEL BALONLARIN TEST EDİLMESİ

Başoğlu, Fatma
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Bu tez çalışmasında, Türk hisse senedi piyasasında Mart 1990-Şubat 2012 döneminde rasyonel balonlar olup olmadığı hisse senedi piyasası fiyat kar payı oranları verileri kullanılarak analiz edilmiştir. Rasyonel balon dönemleri, Phillips, Shi ve Yu (2011a) tarafından geliştirilen, sağ kuyruklu bir birim kök testi olan generalized sup augmented Dickey-Fuller testi aracılığıyla tahmin edilmiştir. Bahsedilen rasyonel balon testi Türk hisse senedi piyasa endeksleri için haftalık fiyat kar payı oranı zaman serilerine uygulandığında, hem referans endekslerinde hem de sektör endekslerinde rasyonel balon varlığı tespit edilmiştir. Belirlenen rasyonel balon periyotları takip eden dönemlerde gerçekleşen Türkiye finansal krizleri açısından erken uyarı sinyalleri olarak düşünülebilinir.

Anahtar Kelimeler: Rasyonel balonlar, sağ kuyruklu birim kök testi, generalized sup augmented Dickey-Fuller test, fiyat kar payı oranı, erken uyarı sinyalleri

To my family and friends

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey-Fuller
BADF	Backward Augmented Dickey-Fuller
GSADF	Generalized Sup Augmented Dickey-Fuller
PSY	Phillips, Shi and Yu
PWY	Phillips, Wu and Yu
SADF	Sup Augmented Dickey-Fuller
SPY	Shi, Phillips and Yu

CHAPTER 1

INTRODUCTION

The recent global financial crisis has led to a recession in the world economy. Due to deregulation and liberalization, when the United States housing bubble burst in the summer 2007, financial markets all around the world faced with sudden drops in stock prices. As the financial systems in the developed and developing economies deteriorated, the regulators and policymakers have been charged with taking strict measures against possible financial crisis. Furthermore, not surprisingly, a growing number of studies have tried to find empirical evidence on the causes of crisis.

Even as liberalization has attracted foreign capital flows into emerging economies, it has also raised costs for investors with increasing financial risk. According to McKinsey Global Institute report released in 2010 [29], the recent crisis has caused diminishing investors’ confidence to capital markets. Investors avoid taking risks in stock markets due to the ever worsening economic conditions. It is also pointed out that, in the coming decade, the capital supply for holding stock will not be enough to fund the amount needed for companies’ growth.

Turkey, as a developing country, has also been affected by its integration in the world financial markets. The Turkish stock market, Istanbul Stock Exchange (ISE), experienced a sharp decline during the U.S. subprime mortgage crisis despite Turkey’s high economic growth rate. Turkey’s fastest-growing economy is still suffering from the negative impact of financial globalization in terms of high current account deficit. Today, the gap between savings and investment is a serious problem threatening the future stability of Turkish economy.

The strict measures taken by the Turkish policymakers and regulators, so far, have not been sufficient to deal with the large account deficit. The new ISE Chairman, Turhan (2012) [43], in his speech during the handover ceremony, stated that the Turkish economic system needs capital market instruments to reduce the deficit while maintaining the economic and financial stability. He pointed out that, however, capital market funds are only equal to one-third of the Turkish national income, not coinciding with the dynamics of Turkey’s economy.

Since the 1990s, Turkey's economy both in real sector and financial sector has been in great troubles because of the economic and financial imbalances. After witnessing significant market volatility, Turkey experienced three severe crises in 1994, 2000 and 2001 that led to the lost of investor confidence in the financial system. A critical strategy to restore confidence in stock markets, as discussed by majority of financial academicians, monitor the signals of financial crisis and take measures to prevent the possible crisis in the future. Hence, one of the main purposes of our study is to provide empirical evidence demonstrating the relationship between the stock market volatility and the financial crises in Turkey.

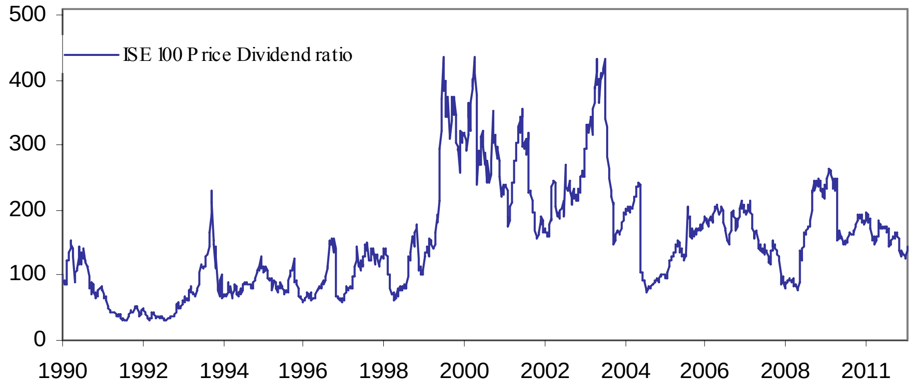

Figure 1.1 The ISE 100 price dividend ratio (normalized to 100 at the starting point)

The general movement of the Turkish stock market is measured by the benchmark index ISE 100 which consists of the most representative stocks of Istanbul Stock Exchange. Figure 1.1 displays the time series of ISE 100 price dividend ratio between the period of March 1990 and February 2012. As Figure 1.1 shows, the price dividend ratio is too volatile, and thus indicates that stock prices cannot be justified by merely discounted value of future dividends. Especially, the ratio is extremely volatile between 1999 and 2004, before plunging down to its normal levels. The peak of this sub-period is 4.36 times bigger than the starting point. However, the most significant increase can be observed in 1994 which is 7.4 times greater than the beginning of this sub-period. Although the Asian and Russian crisis during 1997 and 1998 did not cause a seriously damage in the Turkish economy, the small scale burst and collapse periods can be observed in asset prices. Furthermore, as stated before, the U.S. subprime mortgage crisis in 2008 led to a sharp decline in ISE 100 index.

Given these fluctuations in the Turkish stock market, our main concern is to identify the exuberance behavior in stock market indices. Gilles and Leroy (1992) [17] defined the abnormal discrepancy between market prices and real values of stocks as bubbles. To answer the question how we can distinguish the bubbles from other fluctuations, Komaromi (2006) [25] referred initial displacement, distinct price rise and new buyers as direct bubble indicators and leverage, large number of economic policy signals and corporate scandals as indirect bubble signals. He also indicated that a bubble is only attached to events with negative macroeconomic consequences or crisis.

To detect the exuberance in financial markets, Phillips, Shi and Yu (2011a) [32] proposed a quantitative warning system for market participants and policymakers. In this thesis, their new bubble detection and dating strategies are employed to examine whether the Turkish stock market is driven by rational bubbles over the period from March 1990 to February 2012. Early empirical studies gave conflicting results about the existence of bubbles in the Turkish stock market. However, our study found strong evidence in the favor of existence of rational bubbles not only in benchmark indices but also in sector indices.

The paper is organized as follows: Chapter 2 provides an overview of existing bubble detection methods. Chapter 3 is devoted to the theoretical background of employed methodology. Chapter 4 describes the data and descriptive statistics, and gives empirical test results. Finally, Chapter 5 concludes our main findings.

CHAPTER 2

LITERATURE REVIEW

Rational bubbles occur when an investor buys a stock with the expectation of selling at a higher price to another investor who has the same expectation. The investors stay in the market despite the deviations of prices from fundamentals due to the probability of high return. In the bubble literature, a large number of studies have tried to find an answer to the question about possibility of rational bubbles in asset prices. There have been conflicting results regarding whether they exist or not. Blanchard (1979) [2] and Blanchard and Watson (1982) [3] demonstrated the existence of rational bubbles, the deviations from fundamental value would be possible if all investors are rational. On the contrary, Diba and Grossman (1988a, b) [8, 9] insisted on the absence of rational bubbles.[1]

The central question about existence of bubbles then is: How can one detect the rational bubbles by empirical methods? There is a comprehensive literature on the modeling and detecting rational bubbles. Nevertheless, the literature survey shows that econometric bubble tests cause inconsistent results because of the variety of bubble term specification. The main aim of this literature survey is to provide a general overview of bubble tests based on asset price and bubble models.

The first bubble tests were originally designed to verify present value model of asset prices. According to the present value model, the asset price is determined by the summation of discounted cash flows. Shiller (1981) [38] and Leroy and Porter (1981) [26] pointed out the extreme volatility of stock prices which cannot be explained by future dividends. The stock prices are too volatile to be justified with only present value of cash flows. While they assumed a constant discount rate, Grossman and Shiller (1981) [18] tried to explain the variability of stock prices with real interest rates concerning consumption or economic activity.

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[1] The existence of rational bubbles was also discussed by Obstfeld and Rogoff (1983) [31], Shiller (1984) [39], Tirole (1985) [42], West (1987) [44], Dezhbakhsh and Demırguc-Kunt (1990) [6], Gilles and Leroy (1992) [17], and Rappoport and White (1993, 1994) [35].

The implied price variance bounds by Shiller (1981) [38] were employed for bubble detection purposes first in Blanchard and Watson's studies (1982) [3].[2] They concluded that bubbles cause the violation of bounds by means of additional noise. Subsequently, Campbell and Shiller (1986) [4] found that the price dividend ratio is not enough to explain variation in stock prices. Their model comparison also strongly rejected constant discount rate. West (1988b) [46] considered whether the varying discount rate models proposed by Campbell and Shiller (1986) [4] and West (1988a) [45] are adequate to explain the price volatility and concluded that there is no significant result.

In their earlier studies, West (1987) [44] proposed a bubble test comparing two equations based on constant discount rate model. First, stock prices were regressed on lagged dividends to check the consistency of data with present value model. Then, dividend series were estimated with identified forecasting equation. The stock prices were regressed from estimated dividends and implied discount rates. Rational bubbles were confirmed as the difference between estimated stock prices. However, West pointed out that the difference might be explained with the variation in discount rates. Although West's bubble test was properly designed for both model specification and bubble detection, there are still econometric shortcomings.[3]

The foregoing studies considered bubbles as extraneous deviations from fundamentals. Contrary to this argument, Froot and Obstfeld (1991) [16] introduced the intrinsic bubbles depending only on market fundamentals. Bubbles defined as deterministic function of dividends and detected by the explosive behavior of price dividend ratio. In their nonlinear model specification, they imposed the nonexistence of negative stock prices and employed a geometric random walk dividend process. Wu (1997) [47] criticized their stock price restriction allowing a market in which investors always overvalue securities. He also drew attention to implementation difficulties with more complicated dividend process. Also, Driffill and Sola (1998) [11] showed that a regime switching dividend model is better fitting the data.

The proposed models so far have not specified a bubble term. They defined bubbles generated by extraneous events or just explosive dividends. The following studies incorporated bubbles into the model. Diba and Grossman (1988a) [8] proposed submartingale property for bubble process which implied explosive behavior of rational bubble. Their explosive bubbles start, grow in expectation with discount rate and then explode. Furthermore, given free disposal of shares, their bubbles should be always positive because shareholders cannot rationally expect stock price to

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[2] Shiller's stationary price and dividend assumption and small sample properties of estimators was criticized by Flavin (1983) [13], Kleidon (1986) [24], Marsh and Merton (1986) [28] and Flood, Hodrick and Kaplan (1994) [14].

[3] The detailed discussion about econometric shortcomings can be found in Gürkaynak (2008) [19].

become negative in a finite horizon. This fact indicated that their rational bubbles also cannot burst and restart, if it exists now, it must have initiated at the first date of trading. In their following article, stationary and cointegration tests were employed to detect explosive bubbles from asset prices and observable market fundamentals (Diba and Grossman, 1988b) [9].[4] As we stated earlier, their analysis concluded that stock prices do not contain explosive rational bubbles. However, Evans (1991) [12] demonstrated that above mentioned tests are incapable of detecting bubbles with periodically collapsing property other than explosive.

Evans suggested a new model for a bubble process in which bubble collapses to a nonzero value and starts again with an explosive rate. After Evans' critism, a great deal of researchers has been trying to find a reasonable test for periodically collapsing bubbles. Wu (1997) [47] specified bubble as an unobserved variable and estimated with Kalman filter. He proposed a model allowing negative bubbles as well as positive bubbles. On the contrary, as noted in Gurkaynak (2005) [19], the existence of negative bubbles was strongly rejected due to the theoretical concerns mentioned above (Diba and Grossman, 1988a) [8].

The periodically collapsing dynamics of bubbles was first introduced by Blanchard (1979) [2]. The distinguishing feature of specified bubbles is moving between expanding and collapsing states. In order to detect this behavior, Hall, Psaradakis and Sola (1999) [22] used Markov switching unit root process in which expanding and collapsing periods employed as different regimes. They generalized standard augmented Dickey-Fuller test by allowing parameters to switch between different regimes but under the identical error variance assumption. By empirically examining, Shi (2010) in [36] compared Markov switching model by using constant and time varying variance. His simulations showed that the constant model has inconsistent results in detecting bubble periods.

The bubble detection tests mentioned above have only considered whether a rational bubble could be detected by empirical methods. The most recent studies not only proposed the detection of bubbles but also to locate their emergence and collapse dates. Phillips, Wu and Yu (2011) [33] suggested sup augmented Dickey-Fuller test to improve unit root procedures for bubble detection purposes. The new method used recursive regression techniques based on the augmented Dickey-Fuller (ADF) statistics. As their simulation studies showed, the sup ADF test is better performing to detect periodically collapsing bubbles than cointegration based unit root tests. Homm and Breitung (2011) [23] also compared the sup ADF test with other unit root tests which modified in

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[4] Hamilton and Whiteman (1985) [21] and Diba and Grossman (1984) [7] recommended stationary tests for obtaining evidence against the existence of rational bubbles. Campbell and Shiller (1987) [5] showed that if the present value model is true, the linear combination of prices and dividends is stationary in levels, thus cointegrated.

order to detect bubbles. According to their results, the sup ADF is the most powerful test when there is more than one bubble episode in the sample. However, Phillips, Shi and Yu (2011a) [32] disagreed.

When there are multiple bubble episodes in the data, Phillips, Shi and Yu (2011a) [32] demonstrated that the sup ADF test is not sufficient to detect and locate bubbles. To deal with inconsistencies of the sup ADF test, they generalized the testing procedure by allowing sample sequences over a broader and flexible range. Furthermore, a new dating strategy was proposed based on this generalized sup ADF test. The bubble detection and dating strategies employed in the generalized sup ADF test compared corresponding strategies in the sup ADF test via simulations. In these analyses, the generalized sup ADF test outperformed and identified important bubbles during the sample period. Consequently, in this thesis we shall employ the generalized sup ADF test for the purposes of detecting and locating explosive behavior in the Turkish stock market.

Previously, the bubbles in the Turkish stock market have been empirically analyzed by Altay (2008) [1], Taşçı and Okuyan (2009) [40] and Yanık and Aytürk (2011) [48]. Altay tested the presence of rational bubbles in the ISE 100 and sector indices of Istanbul Stock Exchange. By applying linear and nonlinear unit root tests to the price dividend ratios of the 7 indices, he proved the existence of bubbles in the benchmark and some sector indices between the period 1998 and 2006. On the other hand, Taşçı and Okuyan used parametric and nonparametric duration dependence tests and applied them to the ISE 100 and sector indices.[5] Although their application was implemented for a longer period, they concluded that there is no bubble in the sample data. Yanık and Aytürk also used duration dependence tests to detect rational speculative bubble in the Turkish stock market for the period 2002-2010. Their test results indicated the absence of rational expectations bubbles during the sample period.

These conflicting results motivated a new empirical research on the Turkish stock market with the recent bubble test. For this purpose, we empirically examined whether the Turkish stock market was driven by rational bubbles over the period between March 1990 and February 2012 using generalized sup augmented Dickey-Fuller test. The results showed that rational bubbles exist in the Turkish stock market not only in benchmark indices but also in sector indices.

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[5] McQueen and Thorley (1994) [30] proposed duration dependence test as a bubble detection test.

CHAPTER 3

METHODOLOGY

In this chapter, we will briefly discuss rational explosive bubbles along with Diba and Grossman's conventional cointegration tests and Evans' periodically collapsing bubbles. Then, we will set the basic framework from the papers of Phillips, Wu and Yu (2011) [33], hereafter PWY, and Phillips, Shi and Yu (2011a) [32], hereafter PSY, which are needed to understand our empirical study.

3.1 Rational Explosive Bubbles

The rational expectations model for stock price determination assumes that the expected rate of return from holding a stock should be equal to the constant real rate of return r.[6] Let P_t be asset price at time t and D_t be dividend paid out between the period t and t +1, and then the basic price equation is

$$P_t = \left(\frac{1}{1 + r}\right)\mathrm{E}_t(D_t + P_{t+1}) \quad , \tag{3.1}$$

where E_t represents the conditional expectation based on the information at period *t*. The equation is a first order expectational difference equation. The forward-looking solution to this equation can be derived by applying transversality condition

$$\lim_{i \to \infty}\left(\frac{1}{1 + r}\right)^i \mathrm{E}_t(P_{t+i}) = 0 . \tag{3.2}$$

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[6] We give a brief discussion about the model based on the papers of Diba and Grossman (1988a, b) [8, 9] and Evans (1991) [12].

If the transervality condition holds, then the unique market fundamental solution implies that a stock price should be determined by the discounted value of its expected dividends. Under the assumption that growth rate of expected dividends is smaller than $1 + r$, the fundamental stock price is expressed as

$$P_t^f = \sum_{i=0}^{\infty} \left(\frac{1}{1 + r} \right)^i \mathrm{E}_t \left(D_{t+i} \right) . \tag{3.3}$$

Otherwise, if the transversality condition fails, the deviations from fundamentals can be explained incorporating variable bubbles into the pricing equation. The general solution to the equation (3.1) involves fundamental stock price P_t^f and bubbles B_t, expressed as

$$P_t = P_t^f + B_t \quad , \tag{3.4}$$

where the bubbles B_t can be explained with rational expectations. To make our point clear, bubbles are defined as rational when there are rational investors in the market who pay for the stock more than the fundamental price because of the expectation of selling their shares with a profit. Hence, under the no arbitrage assumption the selling price is equal to the equilibrium price. Diba and Grossman (1988a) [8] proposed following sub-martingale property which restricted the arbitrage opportunities and implied the explosive property of rational bubbles

$$\mathrm{E}_t (B_{t+1}) = (1 + r) B_t . \tag{3.5}$$

This relationship states that the future expectation of bubbles component in stock prices can be accounted for the existence of rational bubbles today. As can be seen from equation (3.5), the bubbles either increase or decrease at the rate of $1 + r$. Accordingly, the stock price takes both positive and negative values depending on the bubbles' direction. However, given free disposal of shares, rational investors do not expect a stock price to become negative in a finite holding period. Diba and Grossman (1988a) [8] ruled out, therefore, the existence of negative bubbles.

Considering the explosive property in equation (3.5), the bubble process satisfy the stochastic difference equation

$$B_{t+1} - (1 + r) B_t = z_{t+1} , \tag{3.6}$$

where z_{t+1} is a random variable whose expected values are always zero, i.e., $\mathrm{E}_{t-i}(z_{t+1}) = 0$ for all $i \geq 0$. Suppose bubbles do not exist at date t, given the non-negativity of bubbles, $B_{t+1} \geq 0$, equation (3.6) implies the variable z_{t+1} should be equal or greater than zero, i.e., $z_{t+1} \geq 0$. Since all expectations of z must be zero, z_{t+1} is equal to zero with probability one. Diba and Grossman pointed out that, therefore, if a bubble exists now, it must have existed since the first day of trading. It is also clear that when bubbles burst, the bubble process cannot restart again.

In their following paper, Diba and Grossman (1988b) [9] proposed a new asset pricing model allowing the effect of unobservable variables on market fundamentals and different valuations of expected dividends and capital gains. The general equation involves the fundamental part justifying the sum of expected dividends and unobservable fundamentals, and the bubbles part:

$$P_t = \sum_{i=0}^{\infty} \left(\frac{1}{1 + r} \right) \mathrm{E}_t \left(\alpha D_{t+i} + U_{t+i} \right) + B_t, \tag{3.7}$$

where U_t represents the unobservable fundamentals and α denotes the relative proportion of expected dividends to expected capital gains. Again, the rational bubbles satisfy explosive property implied in equation (3.5).

To detect the explosive bubbles, they first evaluated the stationarity properties of stock prices and dividends with sample autocorrelations and right-tailed unit root tests which identifies explosive processes as alternative hypothesis. Their argument can be explained as: If the first differences of D_t and U_t are stationary, then P_t should be stationary in the first differences in the absence of bubbles. However, when rational bubbles exist, taking differences of P_t is not sufficient to get stationary series. By empirically examining, they concluded that the explosive rational bubbles do not exist in stock prices.

They also employed conventional cointegration tests based on right-tailed unit root tests to support the abovementioned inference. According to their methodology, in the absence of bubbles, although the price and dividend series are nonstationary, their linear combination should be stationary and then the series cointegrated. The application is done by applying unit root tests to determine the behavior of price and dividend series. In case they are nonstationary, a cointegrating regression between the series is performed to obtain the residual process. If the residual process also shows stationary behavior, it is concluded that price and dividend series are cointegrated. Eventually, their conventional cointegration test results also demonstrated the nonexistence of bubbles in stock prices.

3.2 Evans' Periodically Collapsing Bubbles

Evans (1991) [12] showed that Diba and Grossman's conventional cointegration test is not sufficient to detect the rational bubbles which collapse to a nonzero value and then continue to increase with some explosive rate. He demonstrated by simulations that bubble boom and burst cycle can deceptively behave as stationary during conventional unit root testing. These bubbles can never disappear but they diminish periodically as they reach a threshold.

Evans suggested a new bubble process following the no arbitrage condition as implied in equation (3.5). The proposed bubble process is

$$B_{t+1} = (1+r)B_t \, \varepsilon_{B,t+1}, \qquad \text{if } B_t \leq b, \tag{3.8}$$

$$B_{t+1} = \left[\zeta + \pi^{-1}(1+r)\theta_{t+1}(B_t - (1+r)^{-1}\zeta)\right]\varepsilon_{B,t+1}, \qquad \text{if } B_t > b, \tag{3.9}$$

where $1+r>1$ and $\varepsilon_{B,t} = \exp(y_t - \tau^2/2)$ with $y_t \overset{\text{iid}}{\sim} N\left(0,\tau^2\right)$. In equation (3.9), θ_t measures the probability of collapse and follows Bernoulli process which takes the value 1 with probability π and 0 with probability $1-\pi$, where $0<\pi\leq 1$. Also, the variable ζ refers a positive remaining size of bubble after collapse. When bubble size is equal or smaller than threshold value *b* (i.e., $B_t \leq b$), bubble grows at mean rate $1+r$. Otherwise, if the bubble size is greater than threshold value *b* (i.e., $B_t > b$), bubble grows at a faster mean rate $\pi^{-1}(1+r)$, but bubble might collapse to nonzero value ζ with probability $1-\pi$ and then the process resumes. The bubbles described here are always positive but they periodically collapse.

Of course, Evans' critism was followed by newly emerging econometric methods especially for detecting periodically collapsing bubbles. Most of the studies tried to explain the nonlinear structure of bubbles with the nonlinear models like GARCH, Markov-switching or threshold autoregressive time series models. More recently, PWY and PSY suggested not only bubble detection but also location strategies which can be used as an early warning system for financial markets. Since we employed their tests in our empirical work, the theoretical framework will be discussed in more details. With this purpose, we first give a brief summary of theoretical background of their strategies.

3.3 Augmented Dickey-Fuller Test

Financial data mostly involves nonstationary observations whose means, variances and covariances change over time. The unit root tests are commonly used to determine whether the time series are stationary by using an autoregressive model. The most frequently used unit root procedure Dickey-Fuller test, proposed by Dickey and Fuller (1979) [10], estimates the following first order autoregressive $AR(1)$ regression equation

$$\Delta y_t = \alpha + \beta y_{t-1} + \varepsilon_t, \quad \varepsilon_t \overset{\text{iid}}{\sim} N\left(0, \sigma^2\right), \tag{3.10}$$

where Δy_t denotes the first difference, α is the drift term, and β is the coefficient of model. Here, error term ε_t is a white noise process represented with zero mean and constant variance that is uncorrelated with ε_s for $t \neq s$. Dickey-Fuller test compares the t-statistics of residuals with Dickey-Fuller critical values. The null hypothesis of the Dickey-Fuller test is $H_0 : \beta = 0$ which represents unit root versus the left-tailed alternative hypothesis $H_1 : \beta < 0$ stable root.

If the residuals in first order autoregressive model are still correlated, the test has been augmented by Δy_{t-i} for higher level autoregressive processes. The augmented Dickey-Fuller (ADF) test is applicable for larger and complicated time series. Consider a simple general $AR(k)$ process

$$y_t = \mu + \theta_1 y_{t-1} + \theta_2 y_{t-2} + \ldots + \theta_k y_{t-k} + \varepsilon_t, \tag{3.11}$$

The following regression should be estimated to perform unit root test on the above $AR(k)$ process

$$\Delta y_t = \alpha + \beta y_{t-1} + \sum_{i=1}^{k} \phi_i \Delta y_{t-i} + \varepsilon_t, \tag{3.12}$$

where k is the number of lags added to the model to ensure that the residuals ε_t are white noise, i.e., uncorrelated. Again, the t-statistic on the β coefficient is compared with Dickey-Fuller critical values to determine whether the data is stationary or not. If the process is stationary, then the null hypothesis that β equals zero is rejected. In that case, the alternative hypothesis is confirmed that β is smaller than zero.

As mentioned above, the ADF test employs left-tailed alternative hypothesis to detect unit root in the data. In the preceding section, the right-tailed unit root tests were proposed by Diba and Grossman to identify alternative explosive behavior. However, Evans showed that proposed tests can not deal with nonlinear structure of bubbles. The following studies attempted not only to improve the power of right-tailed ADF tests to detect bubbles but also to discover new bubble dating strategies.

3.4 Sup Augmented Dickey-Fuller Test

The sup augmented Dickey-Fuller test, hereafter SADF, was proposed by PWY (2011) [33] in order to test unit root in explosive processes. The basic fundamental of this test is using recursive regression techniques to test the unit root against the alternative right-tailed explosive hypothesis. In their simulation studies, they demonstrated the overall ability of detecting periodically collapsing bubbles comparing with conventional cointegration tests.

The SADF method specifies the null hypothesis as a random walk process without drift and estimates the regression model with a drift term after determining the lag order k with significance tests. The null hypothesis fails when the regression coefficient β is greater than 0 which implies an explosive process. The respective reduced model under the null hypothesis and estimated regression equations are

$$y_t = y_{t-1} + \varepsilon_t, \quad \varepsilon_t \overset{\text{iid}}{\sim} N\left(0, \sigma^2\right), \tag{3.13}$$

$$\Delta y_t = \alpha + \beta y_{t-1} + \sum_{i=1}^{k} \phi_i \Delta y_{t-i} + \varepsilon_t, \quad \varepsilon_t \overset{\text{iid}}{\sim} N\left(0, \sigma^2\right). \tag{3.14}$$

The above regression model is estimated repeatedly for each subsample which starts always with the first observation but the last point varies. Suppose r_1 is the fractional starting point fixed at *0* and r_2 is the fractional ending point of each sample. The window size r_w, which is equal to $r_2 - r_1$, expands from small window size r_0 and total sample size 1, i.e., $r_2 = r_w$, $r_2 \in [r_0, 1]$. The ADF test statistic is computed for each of these subsamples.

SADF test decides the explosiveness of the process based on the sup value of the ADF statistic sequence by comparing with the right-tailed critical values of its limit distribution. If we denote the ADF statistic $ADF_0^{r_2}$ for the subsample corresponding to $[0, r_2]$, under the null hypothesis, the respective sup ADF statistic is given by

$$\sup_{r_2 \in [r_0, 1]} ADF_0^{r_2} \Rightarrow \sup_{r_2 \in [r_0, 1]} \frac{\int_0^{r_2} \widetilde{W} dW}{\left(\int_0^{r_2} \widetilde{W}^2 \right)^{1/2}} \tag{3.15}$$

where W is standard Brownian motion[7] and $\widetilde{W}(r_2) = W(r_2) - (1/r_2)\int_0^{r_2} W$ is demeaned Brownian motion. [8]

Furthermore, PWY proposed a dating strategy based on the ADF statistics, employing fixed initialization window $[r_1, r_2]$ with $r_1 = 0$ and $r_2 \in [r_0, 1]$. To identify the emergence and collapse dates of exuberance, they suggest comparing the test statistic sequence $ADF_0^{r_2}$ against the right-tailed critical values of the standard ADF statistics. The first observation whose ADF statistic is greater than the critical value is determined as the estimated origination date $\lfloor T\hat{r}_e \rfloor$. Given the minimum duration for a bubble to be longer than $\log(T)$, the estimated termination date $\lfloor T\hat{r}_f \rfloor$ is the first observation after $\lfloor T\hat{r}_e \rfloor + \log(T)$ whose ADF statistic is smaller than the critical value [33]. The fractional origination and termination points are calculated with the equations

$$\hat{r}_e = \inf_{r_2 \in [r_0, 1]} \left\{ r_2 : ADF_{r_2} > cv_{r_2}^{\beta_T} \right\} , \tag{3.16}$$

$$\hat{r}_f = \inf_{r_2 \in [\hat{r}_e + \log(T)/T]} \left\{ r_2 : ADF_{r_2} < cv_{r_2}^{\beta_T} \right\} , \tag{3.17}$$

where $cv_{r_2}^{\beta_T}$ is the right-tailed critical values of the standard ADF t-statistics with corresponding significance level of β_T. The significance level β_T should approach to zero when the sample size *T* goes to infinity. For this reason β_T depends on *T.*

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[7] Frey (2009) [15], A stochastic process $W = (W_t)_{t \geq 0}$ on (Ω, F, P) is *standard Brownian Motion,* if $W_0 = 0$ a.s. and W has continuous sample paths with independent and stationary increments.

[8] PWY (2011) [33], given the limiting Brownian Motion process $\{W(r) : r \in [0,1]\}$, the limiting variate $\varepsilon(r) = \int_0^r WdW / \left(\int_0^r W^2\right)^{1/2}$ corresponding to $ADF_0^{r_2}$ is a stochastic process that evolves with *r*. However, the finite dimensional distribution of $\varepsilon(r)$ given *r* is the same for all $r > 0$ and is the usual unit root limit distribution $\int_0^1 WdW / \left(\int_0^1 W^2\right)^{1/2}$.

PWY also discussed in this paper some econometric issues about the model and applied the model to real price and dividend data. They concluded that the model works well with finite sample and strongly detecting the periodically collapsing bubbles with explosive processes. Based on their working paper, Phillips and Yu (2009) [34] showed that the SADF test is consistent in locating the dates of single bubble episode. Together with, Homm and Breitung (2011) [23] modified the alternative statistics as in the SADF test so as to detect the bubbles. According to the simulation results, the SADF test is chosen as the most powerful test in detecting more than one bubble episode. Whereas, when there are multiple bubbles in the data, PSY (2011a) [32] proved that PWY test has weaknesses to detect exuberance and determine the bubble periods.

3.4 Generalized Sup Augmented Dickey-Fuller Test

Phillips, Shi and Yu (2011a) [32] proposed a new bubble detecting and dating strategy known as generalized sup ADF test, hereafter GSADF, to overcome the weaknesses of SADF test in analyzing multiple bubble episodes. They compared the SADF model and the new model GSADF according to size and power, and simulation results verified the superiority of the generalized model. The key differences between the tests can be seen in Figure 3.1, which is taken from PSY's paper.

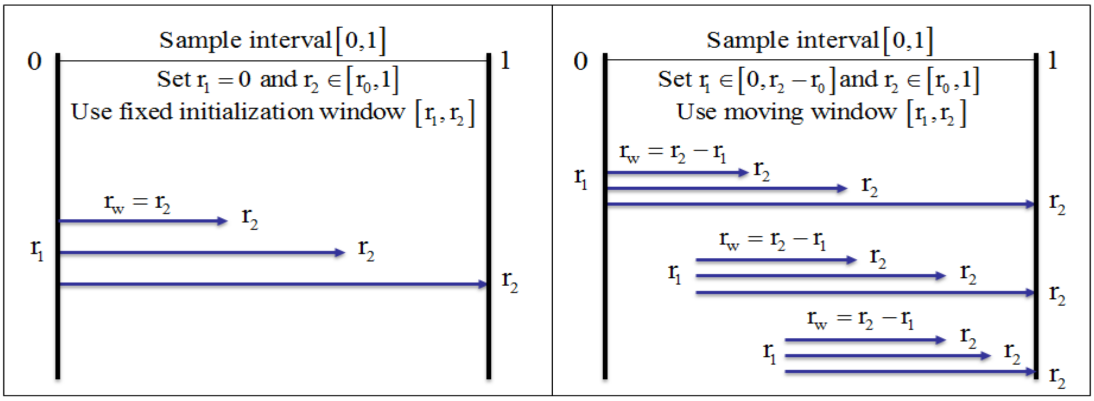
In their earlier studies, Shi, Phillips and Yu (2011) [37], hereafter SPY, examined the specification sensitivities in right-tailed unit root testing to emphasize the importance of hypothesis formulation and regression model specification. Especially, their simulations showed the fact that the asymptotic distributions and critical values used in testing depend on the specified null hypothesis and employed regression model for estimation purposes. The aforementioned null hypothesis for SADF test is also verified as inconsistent. Henceforth, GSADF test employs the null hypothesis and regression model recommended in SPY paper. The specified null hypothesis model is a random walk process with an asymptotically negligible intercept

$$y_t = dT^{-n} + \theta y_{t-1} + \varepsilon_t, \quad \varepsilon_t \overset{\text{iid}}{\sim} N(0, \sigma^2), \; \theta = 1, \tag{3.18}$$

where d is constant and T is sample size with $n > 1/2$. The proposed empirical regression model based on the above null model is

$$\Delta y_t = \alpha_{r_1,r_2} + \beta_{r_1,r_2} y_{t-1} + \sum_{i=1}^{k} \phi^i_{r_1,r_2} \Delta y_{t-i} + \varepsilon_t, \quad \varepsilon_t \overset{\text{iid}}{\sim} N\left(0, \sigma^2_{r_1,r_2}\right), \tag{3.19}$$

where the equation includes a drift term but no deterministic time trend. In the simulation and empirical studies, the null model parameters *d* and *n* are set to unity since the difference between the finite sample distributions is trivial when $n > 1/2$ and $d = 1$.[9] Moreover, the lag order *k* is set to zero so that higher order lags diminish the power of GSADF test and gives rise in significant size distortions.



(a) SADF Test

(b) GSADF Test

Figure 3.1 The sample sequences and window widths of the SADF and GSADF tests

PSY employed recursive regression techniques based on the same idea as in SADF test but with moving window $[r_1, r_2]$ where the fractional starting point r_1 of the sample also changes as if the ending point r_2. The GSADF test proposes a moving r_1 in a range between *0* and $r_2 - r_0$, i.e. $r_1 \in [0, r_2 - r_0]$. As demonstrated, the rising number of regressed samples increases the power of GSADF test statistics. This can be seen as a comparative advantage while detecting multiple bubbles.

The GSADF test implements the right-tailed ADF test repeatedly on a forward expanding sample sequence and concludes inference from the sup function of corresponding ADF statistic sequence. Here, the ADF statistics are calculated based on a broader sample sequence and denoted by $ADF_{r_1}^{r_2}$ for each sample. The GSADF statistics can be defined as the largest ADF statistic over the feasible ranges of r_1 and r_2, i.e.,

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[9] SPY (2011) [37] demonstrated that the discrepancy among finite sample distributions becomes considerable large when n<1/2 but negligible for n>1/2.

$$GSADF(r_0) = \sup_{\substack{r_2 \in [r_0,1] \\ r_1 \in [0, r_2 - r_0]}} \left\{ ADF_{r_1}^{r_2} \right\} \quad . \tag{3.20}$$

When the regression model includes an intercept and the null hypothesis model is a random walk with an asymptotically negligible drift (dT^{-n} with d constant, $n > 1/2$), the GSADF test statistics have the following limit distribution

$$\sup_{\substack{r_2 \in [r_0,1] \\ r_1 \in [0, r_2 - r_0]}} \left\{ \frac{\frac{1}{2} r_w \left[W(r_2)^2 - W(r_1)^2 - r_w \right] - \int_{r_1}^{r_2} W(r)dr \left[W(r_2) - W(r_1) \right]}{r_w^{1/2} \left\{ r_w \int_{r_1}^{r_2} W(r)^2 dr - \left[\int_{r_1}^{r_2} W(r) dr \right]^2 \right\}^{1/2}} \right\}, \tag{3.21}$$

where $r_w = r_2 - r_1$ and W is a standard Brownian motion process. The asymptotic distribution of the ADF statistics is a special case of above equation with $r_1 = 0$ and $r_2 = r_w = 1$ (Hamilton, 1994) [20] while the limit distribution of the SADF statistics is a special case of above equation with $r_1 = 0$ and $r_2 = r_w \in [r_0, 1]$ (SPY, 2011) [37]. The technical details and proofs can be found in the corresponding papers.[10]

In order to identify the dates of explosive behavior, the new date-stamping strategy suggested by PSY uses backward expanding sample sequences. Suppose the fractional ending point fixed at r_2 while the starting point r_1 moves in the range $[0, r_2 - r_0]$. The ADF statistic for each regression with starting r_1 and ending r_2 is denoted by $BADF_{r_1}^{r_2}$ and corresponding ADF statistic sequence by $\left\{ BADF_{r_1}^{r_2} \right\}_{r_1 \in [0, r_2 - r_0]}$. Then the backward SADF statistic is defined as the sup value of the ADF statistic sequence, namely

$$BSADF_{r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} \left\{ BADF_{r_1}^{r_2} \right\}. \tag{3.22}$$

The GSADF statistic can also be defined as the sup value of backward SADF statistic needs to be calculated repeatedly for each r_2 varying from r_0 to *1*, denoted by

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[10] SPY(2011) [37] observed that the limit distributions of ADF, SADF, GSADF move sequentially to the right and become more and more concentrated for a given sample size and the finite sample critical values do not significantly change when the sample size *T* changes.

$$GSADF(r_0) = \sup_{r_2 \in [r_0, 1]} \left\{ BSADF_{r_2}(r_0) \right\}. \qquad (3.23)$$

The new dating strategy compares backward SADF statistics $BSADF_{r_2}(r_0)$ with the right-tailed critical values of corresponding statistics and making inferences about the explosiveness of observations. The estimated origination date $\lfloor T\hat{r}_e \rfloor$ is the first observation whose BSADF statistics is greater than the critical value while the estimated termination date $\lfloor T\hat{r}_f \rfloor$ is the first observation after $\lfloor T\hat{r}_e \rfloor + \delta \log(T)$ whose BSADF statistic is smaller than the critical value. The bubble duration is restricted to be longer than $\delta \log(T)$ where the parameter δ is dependent on frequency of data. The following equations show the formulations of fractional origination and termination points

$$\hat{r}_e = \inf_{r_2 \in [r_0, 1]} \left\{ r_2 : BSADF_{r_2}(r_0) > scv_{r_2}^{\beta_T} \right\}, \qquad (3.24)$$

$$\hat{r}_f = \inf_{r_2 \in [\hat{r}_e + \delta \log(T)/T, 1]} \left\{ r_2 : BSADF_{r_2}(r_0) < scv_{r_2}^{\beta_T} \right\}, \qquad (3.25)$$

where $scv_{r_2}^{\beta_T}$ is the $100\beta_T\%$ critical value of the BSADF statistic based on $\lfloor Tr_2 \rfloor$ observations and β_T is the significance level that goes to zero as the sample size T increases.

In their simulation studies, PSY compared the testing procedure and dating strategies of GSADF and SADF tests in different bubble scenarios. The results showed that, when there are multiple bubble episodes, the latter does not estimate consistently bubbles' origination and termination dates. Furthermore, the empirical application to the real price dividend ratio confirmed the superiority of GSADF test. In all cases, the GSADF method outperformed and identified the important bubble periods in the sample data.

CHAPTER 4

EMPIRICAL RESULTS

In this chapter, after introducing the data, we will discuss the basic descriptive statistics and stationarity test results for benchmark indices. Then, we will present the market and sector results of our empirical study and evaluate the main findings.

4.1 Data and Descriptive Statistics

The data consist of weekly observations on price dividend ratio for the ISE 100 index and Datastream Total Market index as well as the following sector indices: Industrial, Basic Materials, Consumer Goods, Consumer Services, Financial and Technology.[11] The price and dividend yield time series are obtained from *Datastream International* and sampled as weekly taking the Friday closing prices. The tests are applied for the sample period from March 1990 to January 2012, comprising 1144 weekly observations excluding Consumer Services and Technology indices starting in June 1992.

Datastream calculates its own aggregate sector and market price indices. Sector and market aggregations are weighted by market value and are calculated using a representative list of shares. The following equation expresses how the price index is calculated:

$$I_t = I_{t-1} * \frac{\sum_{1}^{n}(P_t * N_t)}{\sum_{1}^{n}(P_{t-1} * N_t * f)}, \qquad I_0 = 100, \tag{4.1}$$

where I_t represents index value on day *t*, I_{t-1} is index value on previous working day, P_t is unadjusted price on day *t*, P_{t-1} is unadjusted price on previous working day, N_t is number of shares on day *t*, f is adjusment factor for a capital action occurred on day *t* and *n* is number of

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[11] The ISE sector indices are not employed because of the unavailable dividend data. Together with, ISE began to calculate sector indices in last years and the calculated periods do not correspond to each other with the aim of comparison.

constituents in index. Datastream dividend yield is derived by calculating total dividend amount and expressing it as a percentage of the market value for the constituents:

$$DY_t = \frac{\sum_1^n (D_t * N_t)}{\sum_1^n (P_t * N_t)} * 100 , \tag{4.2}$$

where DY_t denotes aggregate dividend yield on day *t*, D_t is dividend per share on day *t*, N_t is number of shares in issue on day *t*, P_t is price on day *t* and *n* is number of constituents in index [41].

The ISE 100 index is a capitalization-weighted index consisting of the stocks which are selected from the National Market companies. The stocks are chosen according to total market value of shares outstanding and their daily average traded value. Similarly, Datastream market indices represent the top stocks in the Turkish market covering at least 75% of total market capitalization.[12] All the time series are deflated with consumer price index (CPI), as used in most studies, to convert the nominal data to real data. Turkey monthly CPI data is also taken from *Datastream International*. The general behavior of ISE 100 price dividend ratio can be seen in Figure 1.1. Here, we also present the Datastream Total Market price dividend ratio in the following figure.

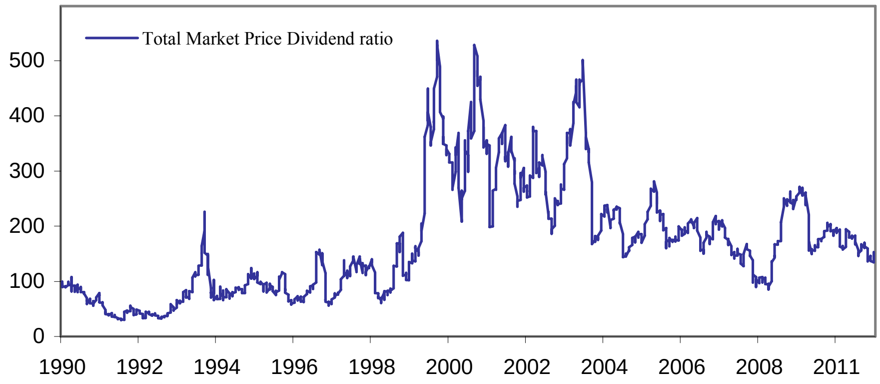

Figure 4.1 The Total Market price dividend ratio (normalized to 100 at the starting point)

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[12] Stocks are allocated to industrial sectors using the industry classification benchmark (ICB) jointly created by FTSE and Dow Jones, and then the sector indices are calculated.

As shown in the graphs, the boom and burst cycles are almost identical in the two indices. However, in the subperiod between 1999 and 2004, Total Market price dividend ratio shows sharper peaks and drops. Also, the results of present empirical study demonstrate that two indices behave similar in an explosive manner except this subperiod. Before we provide the empirical evidence, taking a closer look at the descriptive statistics helps to understand the main features of the analyzed time series.

Table 4.1 Descriptive statistics of price dividend ratio[13]

Series	$Med(P/D)$	$\hat{\sigma}(P/D)$	$Skew(P/D)$	$Kurt(P/D)$	$\hat{\rho}(P/D)$
ISE 100	35.714	21.797	0.904	3.432	0.986
Total Market	39.840	26.849	0.949	3.423	0.989

Note: $Med(P/D)$ is the median of price dividend ratio, $\hat{\sigma}(P/D)$ is the standard deviation of price dividend ratio, $Skew(P/D)$ is the skewness and $Kurt(P/D)$ is kurtosis of price dividend ratio. $\hat{\rho}(P/D)$ is the first order autocorrelation of price dividend ratio with 95% confidence level.

Table 4.1 reports the descriptive statistics of price dividend ratio for ISE 100 and Total Market indices. The median and standard deviation of ISE 100 series are clearly lower than the corresponding statistics of Total Market series. By looking at the skewness and kurtosis coefficients, we can also indicate that the price dividend ratio series are not normal. In fact, the distributions of series are skewed to the right and leptokurtic with long and fat-tails which are widely accepted in the literature as signs of bubbles (Lux and Sornette, 1999) [27]. Moreover, for the first order autocorrelation the sample coefficients are fairly high, i.e., close to 1, while nonstationary series have a unit coefficient on the lagged variable.

Concerning the largest autocorrelation coefficients in the neighborhood of unity, we employ Dickey-Fuller test in order to look at the stationarity of series. Furthermore, as mentioned before, the limit theory and test statistics are sensitive to the specification of null hypothesis and regression model (SPY, 2011) [37]. So, we analyze 3 cases of augmented Dickey-Fuller test for ISE 100 and Total Market price, dividend and price dividend ratio series. Table 4.2 shows the results of augmented Dickey-Fuller test under the different null and alternative hypothesis.

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[13] Descriptive statistics are calculated by using the original values of price dividend ratio. The price dividend ratio series in Figure 1.1 and 4.1 are normalized to 100 at the starting point.

Table 4.2 Augmented Dickey-Fuller test results

	ISE 100			Total Market		
Series	P_t / D_t	P_t	D_t	P_t / D_t	P_t	D_t
	Dickey-Fuller test statistics					
dfARTest	-1.305	-1.235	-1.446	-1.189	-1.184	-1.502
	(-1.942)	(-1.942)	(-1.942)	(-1.942)	(-1.942)	(-1.942)
	0	0	0	0	0	0
dfARDTest	-2.843	-3.107	-2.724	-2.451	-2.864	-2.525
	(-2.865)	(-2.865)	(-2.865)	(-2.865)	(-2.865)	(-2.865)
	0	1	0	0	0	0
dfTSTest	-3.082	3.472	-2.726	-2.614	-3.367	-2.356
	(-3.414)	(-3.414)	(-3.414)	(-3.414)	(-3.414)	(-3.414)
	0	1	0	0	0	0

Note: dfARTest and dfARDTest, under the null hypothesis, assume that a zero drift unit root process underlying the series. As alternative, while dfARTest estimate an autoregressive regression model without drift, dfARDTest estimate the regression model with drift. The dfSTTest estimates the regression model including a time trend with drift term based on the null hypothesis that a unit root process with arbitrary drift.
The numbers in parentheses represent the corresponding critical values at the 95% significance level. Hypothesis 0 denotes the nonstationary series versus 1 starionary series.

Statistically speaking the test fails to reject the unit root null hypothesis H_0 when the test statistic is greater than the corresponding critical value. According to the test results, the price dividend ratio and dividend series are nonstationary in all cases. However, ISE 100 price series show inconsistent results with the different hypothesis. Hence, the unit root test results of price data can be deceptive in making inferences. In our study, therefore, we analyze price dividend ratio to detect rational bubbles. The ratio is calculated by dividing the total market value for the constituents of index by the total dividend amount paid for those constituents' shares.

Assuming the rational expectation theorem, the stock prices deviate from their fundamental values when prices rise above the value justified by their expected dividends. Then, stocks are considered to be overvalued when the price dividend ratio is higher than its fundamental level. In the next section, therefore, the right-tailed unit root tests are implemented for the price dividend ratio which can be used as a clear measure of stock price deviations.

4.2 Empirical Results for the ISE 100 and Total Market Indices

We employ the GSADF test to detect rational explosive bubbles in the Turkish stock market. So far, the empirical studies show conflicting results about the existence of rational bubbles in the ISE 100 and sector indices. Furthermore, the bubble periods in the Turkish stock market have never been identified empirically. For this purpose, we examine not only the existence of bubbles but also locate the bubble origination and termination dates over the 22-year sample period.

In this section, the GSADF test is applied to the ISE 100 and Total Market price dividend ratio series for the period from March 1990 to January 2012, constituting 1244 weekly observations. In our experiments a minimum window size of 52 observations seems to work best considering the power of statistics and test results. Table 4.3 shows the GSADF test statistics for the price dividend ratio series along with their respective finite sample critical values.

Table 4.3 The GSADF test results for the ISE 100 and Total Market indices

	ISE 100	**Total Market**
GSADF statistics for price dividend ratio	7.98	7.85
Finite sample critical values		
90%	2.28	2.28
95%	2.53	2.53
99%	2.99	2.99

Note: The finite sample critical values are obtained from Monte Carlo simulations based on 2,000 replications and smallest window size 0.04 (52 observations).

From Table 4.3, the GSADF statistics for ISE 100 and Total Market price dividend ratio, 7.98 and 7.95, are greater than their respective right tail critical values 2.99 at the level of significance 1%. According to these statistics, it is concluded that there are rational explosive bubbles in the Turkish stock market between the years 1990 and 2012. By taking the evidence of bubbles, now we can identify the bubble periods. To locate the origination and termination dates, the SADF test is performed on the backward expanding sample sequence. Then, corresponding backward SADF statistic sequence is compared with sup ADF critical value sequence at 95% confidence level. As mentioned before, the bubble duration is restricted to be longer than $\delta \log(T)$ where the parameter δ is dependent on frequency of data [32]. So, we determine the minimum duration of bubble period as 8 weeks, approximately two months.[14]

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[14] The Matlab programs for implementing this test are available for download from **https://sites.google.com/site/shupingshi/PrgGSADF.zip?attredirects=0&d=1**. In the present study, all the tests are performed with Matlab.

The top graph in Figure 4.2 represents the identified bubble periods for ISE 100 index, and the bottom graph represents the bubble periods for Total Market index. As the graphs shows, the location strategy identifies the bubble periods Sep93-Jan94 and Dec99-Feb00 for both indices while the bubble period Mar-May00 can be observed only in Total Market data. Hereafter, we will evaluate the located bubble periods in conjunction with their macroeconomic consequences or crisis.

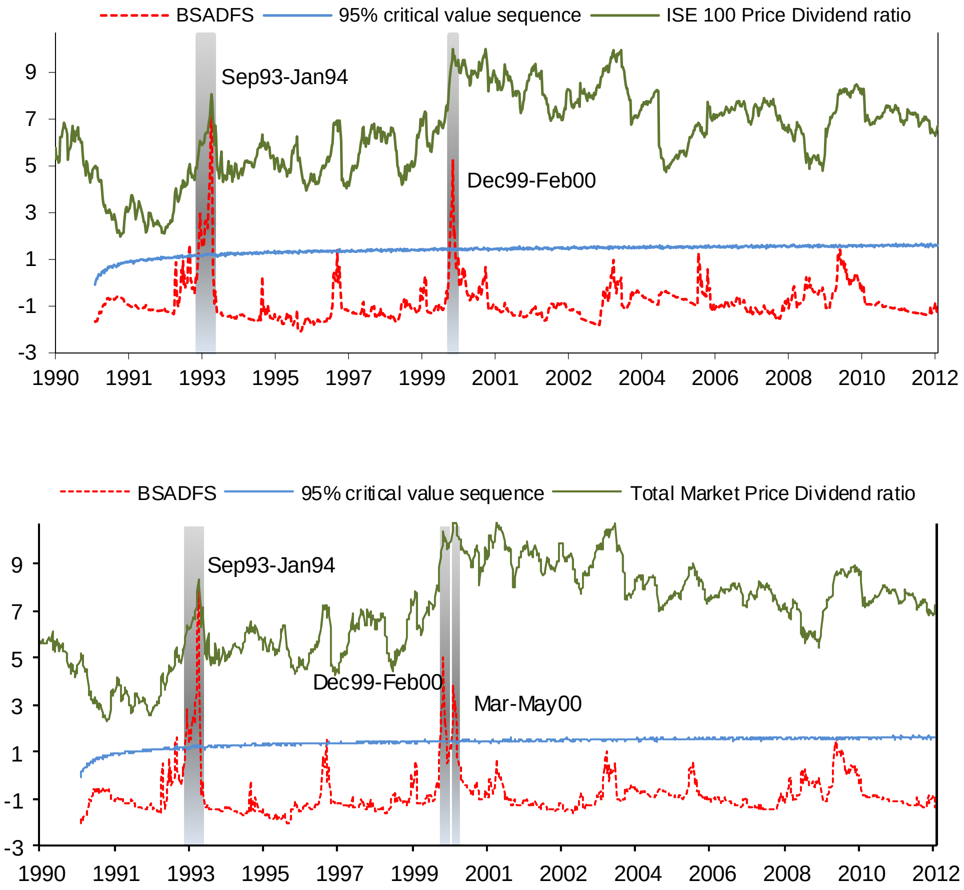

Figure 4.2 Bubble periods in ISE 100 and Total Market price dividend ratio

As expected, the 5-month bubble period between the years 1993 and 1994 was followed by the Turkish financial crisis in the second quarter of 1994. Furthermore, Turkey's 2000-2001 financial crises should be triggered by the boom and subsequent crash in asset prices during the periods Dec99-Jan00 and Mar-May00, on average lasting 2 months. In more recent years, there is no significant bubble in the benchmark indices despite the global crisis.

4.3 Empirical Results for the Sector Indices

In this part of the empirical study, the GSADF test is performed using weekly price dividend ratio series of the Turkish sector indices. [15] The analyzed data covers the period between March 1990 and January 2012 for Industrial, Consumer Goods, Basic Materials and Financial sector indices while the sample period for Consumer Services and Technology indices starts in June 1992. Table 4.4 displays the test results for sector data.

Table 4.4 The GSADF test results for the sector indices

	Industrial	**B.Materials**	**C.Goods**	**C.Services**	**Financial**	**Technology**
GSADF statistics for price dividend ratio						
	7.24	12.62	8.65	7.36	6.16	16.65
Finite sample critical values						
90%	2.28	2.28	2.28	2.23	2.28	2.23
95%	2.53	2.53	2.53	2.49	2.53	2.49
99%	2.99	2.99	2.99	2.97	2.99	2.97

Note: The sector indices Industrial, Basic Materials, Consumer Goods and Financials have 1144 observations while Consumer Services and Technology indices have 1023 observations. The finite sample critical values are obtained from Monte Carlo simulations based on 2,000 replications and smallest window size 0.04 (52 observations).

As shown in the table, the test statistics for price dividend ratio are all well above their respective 1% critical values. Accordingly, the GSADF test results provide the evidence of bubbles in all sector indices. For sector data, the located bubble periods can be seen in the following figures. By considering the differences in economic dynamics of sectors, the impacts of bubbles are evaluated for each sector separately.

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[15] Comparing the Datastream and the ISE sector indices with respect to constituents, we suggest Industrial, Basic Materials and Consumer Goods indices as being representative for ISE Industrial index.

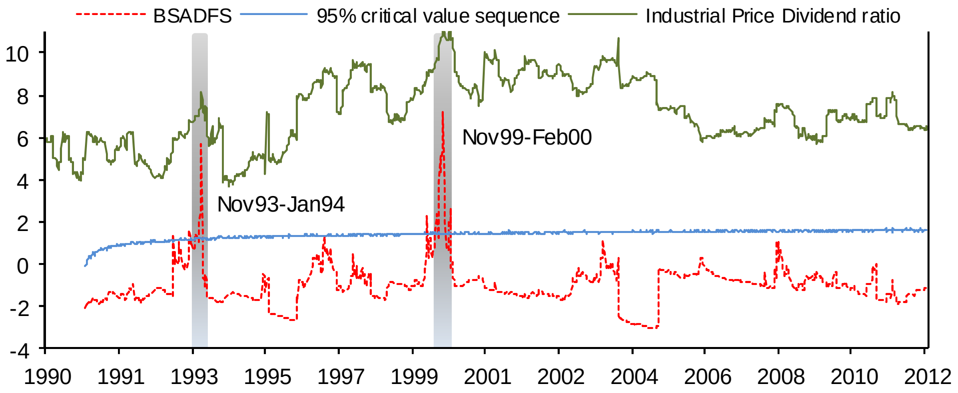

Figure 4.3 Bubble periods in Industrial price dividend ratio

Industrial index includes the most representative stocks of companies in construction and materials, and industrial goods and services. From Figure 4.3, the located bubble periods for Industrial price dividend ratio are Nov93-Jan94 and Nov99-Feb00. Before 1994 crisis, Industrial sector coupled with the bubble over 3 months. Moreover, the Industrial bubble between the years 1999 and 2000, lasting more than 3 months, should lead to the Turkey's 2000-2001 financial crises.

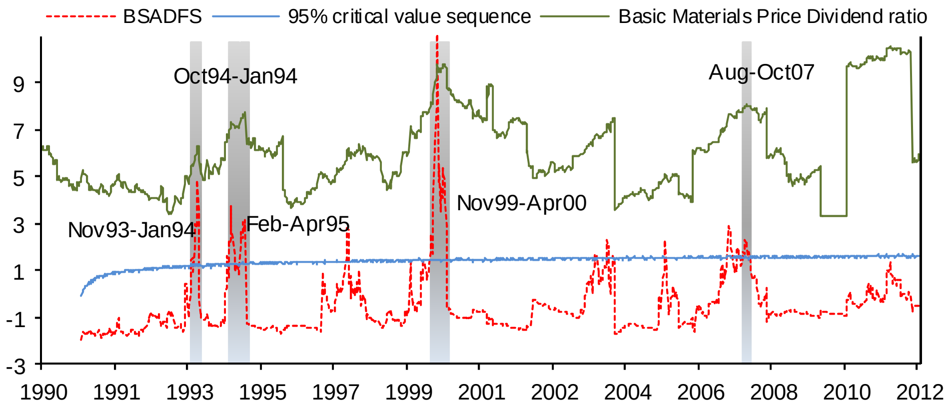

Figure 4.4 Bubble periods in Basic Materials price dividend ratio

The Basic Materials sector index measures the performance of industrial companies engaged in extracting and processing of chemicals and basic resources. As can be seen from the above figure, the sector not only faced with a bubble for 2 months before 1994 crisis but also the bubble lasting 4 months following the crisis. The sector also suffered the pre-crisis bubble during the period between November 1999 and April 2000, persisting more than 5 months. Interestingly, the U.S. housing bubble have been only realized in Basic Materials sector that having a bubble between August and October 2007.

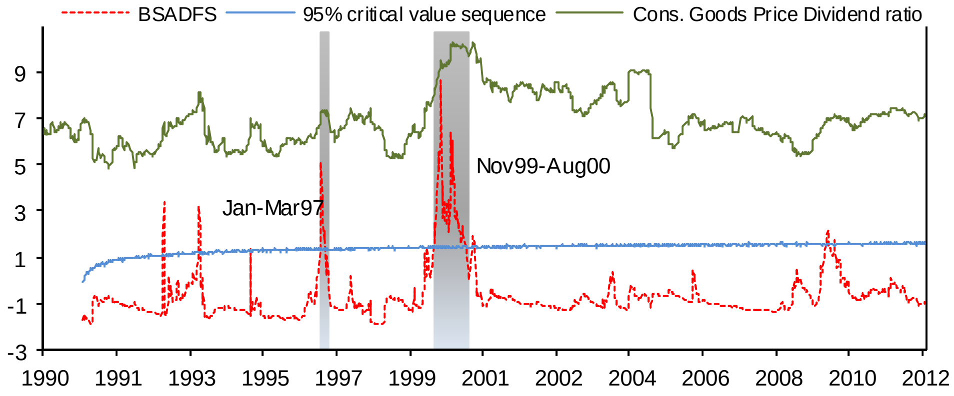

Figure 4.5 Bubble periods in Consumer Goods price dividend ratio

After the severe financial crises in 2000 and 2001, the Turkish economy has been growing rapidly leading to the expansion of Consumer Goods and Consumer Services sectors. Consumer Goods sector includes the companies involved in food/beverage, household/personal goods and automobiles industries, and Consumer Services sector consists of companies engaged in providing retail, media and travel/leisure services.

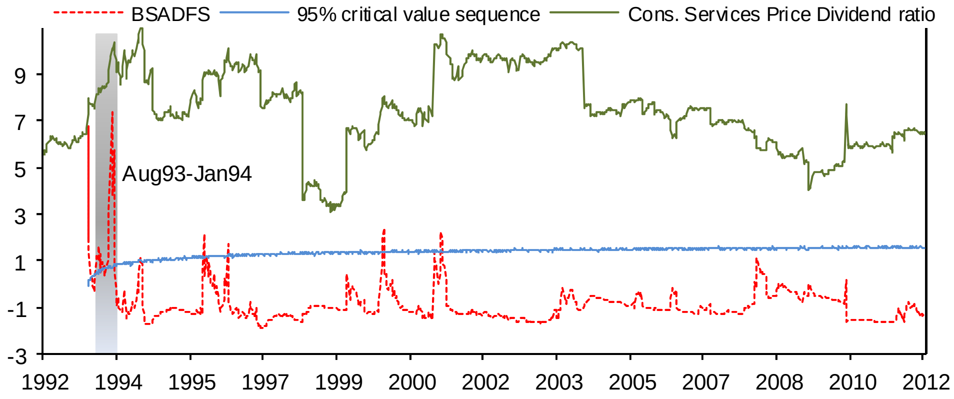

Figure 4.6 Bubble periods in Consumer Services price dividend ratio

From Figure 4.5, the located bubble periods in Consumer Goods index are Jan-Mar97 and Nov99-Aug00. The effect of the 1997 Asian crisis on Turkish economy can be seen in the Consumer Goods sector which experienced a bubble over 2 months just before the crisis. The sector was also exposed to a bubble between the years 1999 and 2000, persisting more than 10 months, while the corresponding bubble duration in the benchmark indices was on average 3 months. As a rising star in the Turkish economy, the Consumer Services sector has only faced with the bubble leading to the 1994 crisis, but lasting almost 6 months.

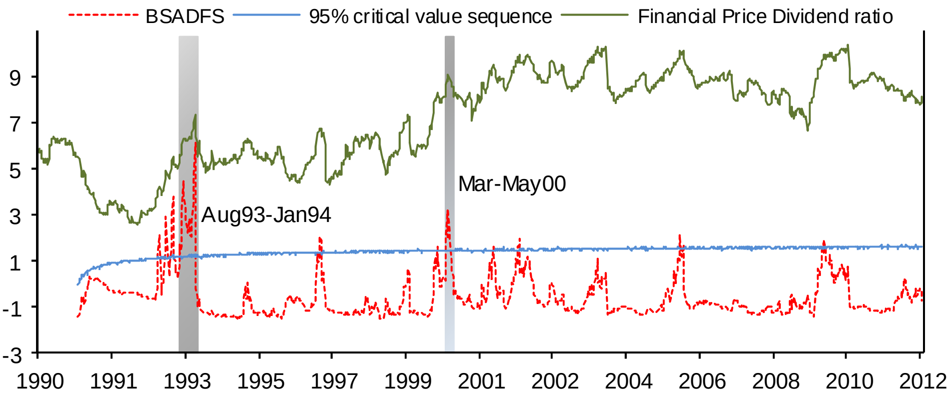

Figure 4.7 Bubble periods in Financial price dividend ratio

We examine above the key real sectors in the Turkish economy. Also, Financial sector has a significant role in providing banking, insurance, real estate and investment funds services to the real economy. Although the sector helps the sustainable growth of the economy, both private and public banks have been blaming for triggering the Turkish financial crises. Indeed, Financial sector coupled with a bubble over 5 months before 1994 crisis and the bubble between the period March and May 2000 leading to Turkish 2000-2001 crisis.

With the rapid speed of technological developments, Technology sector in Turkey has also been affected by universal stock market bubbles. The bubble experienced in the early 1997 was followed by the Asian crisis which has caused severe damage on emerging economies. During the Dot-com bubble in 2000, Technology sector suffered a severe bubble over 10 months, which also triggered the Turkish crisis in 2000 and 2001. Moreover, the recent bubble between the period November 2009 and April 2010 can perhaps be explained by the global financial crisis in 2008.

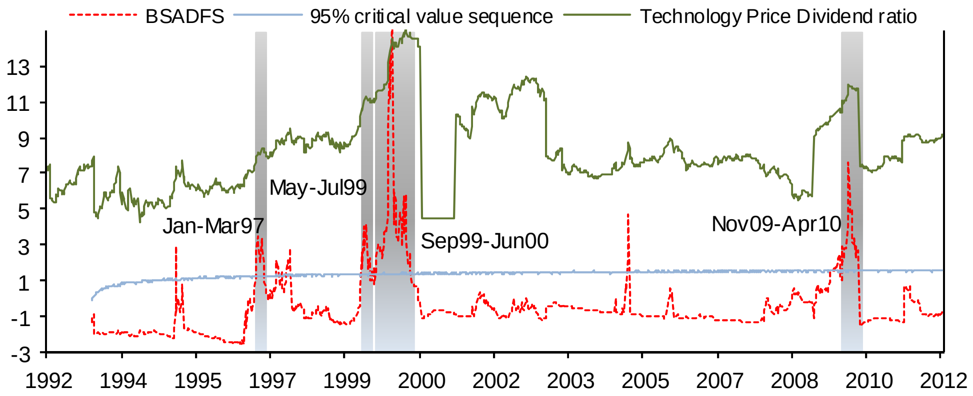

Figure 4.8 Bubble periods in Technology price dividend ratio

To sum up, by detecting and locating bubbles in sector indices of Turkish stock market, our analysis find that the identified bubbles and duration of bubble periods show differences within the sectors of economy. As the located bubble periods for Industrial, Basic Materials and Financial sectors coincide with the pre-crisis bubbles in benchmark indices, the Consumer Services sector has only faced with the bubble before 1994 crisis. On the other hand, Consumer Goods, Basic Materials and Technology sectors have been affected by the international crisis besides the Turkish 2000-2001 financial crises.

CHAPTER 4

CONCLUSIONS

Since the 1990s, Turkey has experienced three financial crises in the years 1994, 2000 and 2001 leading to the severe damage in economic growth. To take measures against the possible crisis in the future, our study focused on the detection of exuberant behavior in the Turkish stock market. Using the recent bubble test GSADF, we empirically examined whether the Turkish stock market was driven by rational bubbles over the period between March 1990 and February 2012. Although previous studies have demonstrated conflicting results, we found strong evidence in the favor of existence of rational bubbles in the Turkish stock market not only in benchmark indices but also in sector indices.

Furthermore, our located bubble periods for the benchmark indices are found to be related with severe financial crises that occurred in Turkey during the sample period. On the other hand, the empirical findings demonstrated that the identified bubbles and duration of bubble periods show differences within the sectors of economy. However, the location strategy is mostly sufficient in identifying bubble periods leading to the subsequent crises. These indicators can perhaps be used as an early warning system to predict the financial crisis.

The findings may provide guidance for the policymakers and regulators who should take into account explosive behavior in the Turkish stock market to prevent a more severe crisis and more damage to economic growth in the future. In this thesis, we discussed the rational explosive bubbles in conjunction with their macroeconomic consequences or crisis. Further research can be done to determine the economic factors causing the rational bubbles.

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