FORECASTING THE PRICES OF NON-FERROUS METALS WITH GARCH MODELS

&

VOLATILITY SPILLOVER FROM WORLD OIL MARKET TO NON-FERROUS METAL MARKETS

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF SOCIAL SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

BURÇAK BULUT

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF BUSINESS ADMINISTRATION
IN
THE DEPARTMENT OF BUSINESS ADMINISTRATION

AUGUST 2010

Approval of the Graduate School of Social Sciences

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ABSTRACT

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August 2010, 51 pages

In the first part of this thesis the prices of six non-ferrous metals (aluminum, copper, lead, nickel, tin, and zinc) are used to assess the forecasting performance of GARCH models. We find that the forecasting performances of GARCH, EGARCH, and TGARCH models are similar. However, we suggest the use of the GARCH model because it is more parsimonious and has a slightly better statistical performance than the other two.

In the second part, the prices of six non-ferrous metals and the price of crude oil are used to examine the dynamic links between oil and metal returns by using the BEKK specification of the multivariate GARCH model and the Granger causality-in-variance tests. Results of our study agree with the previous studies in that the crude oil market volatility leads all non-ferrous metal markets.

In order to move as far away from the effects of 9/11, daily data for the period December 12, 2003 – December 15, 2008 is used for the data analysis part of the thesis.

Keywords: Non-ferrous metal prices, Crude oil prices, GARCH models, Forecasting, Causality-in-variance

ÖZ

KAPSAMLI ARCH MODELLERİ ARACILIĞIYLA DEMİR İÇERMEYEN METAL FİYATLARINDA FİNANSAL TAHMİN DEĞERLENDİRMESİ

&

DÜNYA PETROL PİYASASINDAN DEMİR İÇERMEYEN METAL PİYASALARINA VOLATİLİTE YAYILMASI

Bulut, Burçak

Yüksek Lisans, İşletme Bölümü

Tez Yöneticisi: Doç. Dr. Uğur Soytaş

Ağustos 2010, 51 sayfa

İki bölümden oluşan bu çalışmanın ilk bölümünde, altı demir içermeyen metalin fiyatları (alüminyum, bakır, çinko, kalay, kurşun, ve nikel) kullanılarak 3 farklı ARCH modelinin finansal tahminlerdeki başarı dereceleri karşılaştırılmaktadır. Bu çalışmadan çıkan sonuçlara göre, kapsamlı ARCH (GARCH), üstel GARCH (EGARCH), ve eşik GARCH (TGARCH) modellerinin finansal tahminlerdeki başarı dereceleri birbirine yakın seviyededir. Fakat GARCH modelinin kullanılması tarafımızca daha uygundur, çünkü GARCH modeli daha kolay ve basit olup, diğer iki modele göre kısmen daha iyi sonuçlar vermektedir.

Çalışmanın ikinci bölümünde, yine aynı altı demir içermeyen metalin fiyatları ve ham petrol fiyatları arasındaki ilişki iki değişkenli BEKK modeli kullanılarak araştırılmıştır. Diğer taraftan, metal fiyatları ve petrol fiyatları arasındaki volatilite yayılma etkileri Cheung ve Ng (1996)'nin çalışmalarındaki varyansta nedensellik testleri kullanılarak incelenmiştir. Analiz sonuçları geçmişte yürütülmüş olan

çalışmaları onaylar nitelikte olup, ham petrol piyasalarının tüm demir içermeyen metal piyasalarını yönlendirdiğini göstermektedir.

Veri seti resmi tatiller ve hafta sonları hariç, 12 Aralık 2003 ve 15 Aralık 2008 arasındaki günlük veriyi kapsamaktadır

Anahtar Kelimeler: Demir içermeyen metal fiyatları, ham petrol fiyatları, GARCH modelleri, Finansal tahminler, Varyansta Nedensellik Testleri

To My Parents and Sister

ACKNOWLEDGMENTS

The author wishes to express his deepest gratitude to his supervisor Assoc. Prof. Dr. Uğur Soytaş who had encouraged for the writing of this thesis and who guided, advised, and especially provided the insight in the analysis of the findings.

The author would also like to thank Assoc. Prof. Dr. Ramazan Sarı for his suggestions and comments.

The technical assistance of Dr. Erk Hacıhasanoğlu, by providing the data set that has been used in this thesis, is gratefully acknowledged.

The author would also like to thank his professors, managers and colleagues for their suggestions and support during the creation and release of this thesis.

I am thankful to my beloved parents who taught me the value of education. Special thanks are due to my sister whose understanding that has been profound throughout the difficult times of this master program. Last but not least, thanks to my friend, Müge Kaltalıoğlu for sharing her experience of the dissertation writing and endless support to complete my thesis.

Thanks to everybody who has contributed to my life in a meaningful way. Without your support I am pretty sure that I would not have been able to achieve that much.

TABLE OF CONTENTS

PLAGIARISM iii
ABSTRACT iv
ÖZ vi
DEDICATION viii
ACKNOWLEDGMENTS ix
TABLE OF CONTENTS x
LIST OF TABLES xii
CHAPTER
1.GENERAL INTRODUCTION 1
2.FORECASTING THE PRICES OF NON-FERROUS METALS WITH GARCH MODELS 5
2.1. Introduction 5
2.2. Literature Review 7
2.2.1. Volatility Modeling 7
2.2.2. Forecasting Metal Prices 11
2.3. Data & Methodology 12
2.3.1. Data 12
2.3.2. Time Series Properties of the Data 13
2.3.3. ARMA (p,q) – EGARCH (1,1) 14
2.3.4. ARMA (p,q) – GARCH (1,1) 15
2.3.5. ARMA (p,q) – TGARCH (1,1) 16
2.3.6. Forecasting 17
2.4. Empirical Results 17
2.5. Summary and Conclusions 24

3.VOLATILITY SPILLOVER FROM WORLD OIL MARKET TO NON-FERROUS METAL MARKETS 25
3.1. Introduction 25
3.2. Literature Review 27
3.3. Data & Methodology 36
3.3.1. Data 36
3.3.2. Methodology 37
3.4. Empirical Results 40
3.5. Summary and Conclusions 44
REFERENCES 45

LIST OF TABLES

Table 2.1 - Unit root test results..18
Table 2.2 - EGARCH Results..20
Table 2.3 - GARCH Results..21
Table 2.4 - TGARCH Results..22
Table 2.5 - EGARCH Forecast Statistics...23
Table 2.5 - GARCH Forecast Statistics...23
Table 2.5 - TGARCH Forecast Statistics...23
Table 3.1 - Descriptive statistics for log returns..41
Table 3.2 - Unit root test results..42
Table 3.3 - Results of the bivariate GARCH models...................................43
Table 3.4 - Granger causality-in-variance test statistics.............................44

CHAPTER I

GENERAL INTRODUCTION

In econometrics, one of the most active research areas has been the volatility of time series for the last two decades. The area of time series econometrics that is dealing with volatility research has not been just limited to estimation issues, statistical deduction, and model selection. Mainly, portfolio allocation, option pricing, and risk management issues in financial economics have been resolved by volatility research. Economists, especially who are interested in decision making under uncertainty, particularly focused on volatility, as a measure of uncertainty. Today's financial markets are more interrelated and integrated as a result of increased globalization as well as developments in technology. The information spillovers from one market to another are enhanced with the help of these developments. Empirical studies are triggered in response to these developments and information transmission mechanisms are studied. The pioneers of this research area focus on the prices or returns spillover effects between futures and its underlying cash markets and across markets. Aforementioned researches find that relationship between the futures and its underlying cash market indicates that cash prices are mostly affected by the time futures prices. Moreover, empirical results show significant cross-markets interactions in terms of pricing information transmission across markets.

Many conventional methods for measuring risk are done through studies of the variance (volatility) of the commodity under study. A naive assumption in the theory of financial returns suggests that a stationary time series model with stochastic volatility structure is followed by the returns. This implies that returns are not necessarily independent over time. Engle (1982) propose the Autoregressive Conditional Heteroscedasticity (ARCH) process which has time varying conditional variance. However, according to the empirical results, in order to catch the dynamic of the conditional variance, high ARCH order has to be selected. The high ARCH order implies that researchers have to deal with many parameters and the calculations are very tedious. Bollerslev (1986) proposes as a natural solution to the problem with the high ARCH orders which is the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. This model dramatically reduces the infinite number of estimated parameters to just a few parameters which is mainly based on an infinite ARCH specification. Since then the GARCH models have been very popular for forecasting time varying variance of a time series. Several studies test the accuracy of volatility forecasts by using various error statistics and hypothesis testing. Out of all volatility models, the GARCH models consistently performed better than other volatility models in forecasting volatility.

There has been a surge of interest on the commodity prices as alternative investment areas. This line of research mainly focuses on prices of precious metals and ferrous metals, but non-ferrous metals are not that widely studied. In the first part of this thesis we investigate the univariate models for prices of six non-ferrous metals. We find that the price series contain time varying variance. Then we assess the forecasting performance of GARCH models for aluminum, copper, lead, nickel, tin, and zinc future prices in LME. We employ daily data for the period December 12, 2003 – December 15, 2008 and model the volatility process via GARCH, EGARCH, and TGARCH models. We find that the forecasting performances of all three models are similar. However, we suggest the use of the GARCH model because it is more parsimonious and has a slightly better statistical performance than the other two.

Recently, investors, traders, policy makers and producers are mostly interested in metals and crude oil, partly because of the co-movement of their prices and increases in their economic uses. Using crude oil as a hedge against increasing risk in the metal markets sparked a movement towards closely monitoring crude oil prices as risk management tools in hedging speculative and hedging purposes. The major markets for metals futures contracts are the Commodity Exchange of New York (COMEX), Chicago Board of Trade (CBOT), and the New York Merchantile Exchange (NYMEX). The London Metal Exchange (LME) is the world's largest market for forward contracts in non-ferrous metals, and is also an exchange for spot transactions where physical delivery takes place. In order to study the relations between the volatilities and co-volatilities of several markets, the most frequently applied method is the multivariate GARCH (MGARCH) models. Are the volatilities of common markets directed by the volatility of one dominant market? Is there a direct information transmission mechanism (through its conditional variance) or indirect transmission mechanism (through its conditional covariance) between the volatilities of two assets? Does an increase in the volatility of a market caused by a change in another market, and how much is the extent of this interaction? Are negative and positive shocks leads to similar consequences? A multivariate model can be directly used in order to study such, and multivariate models raise the question of the specification of the dynamics of covariance or correlations. In recent studies the MGARCH models have been used to assess the impact of volatility in financial markets on real variables, such as exports, imports and/or growth rates, and the volatility of these variables. In order to study the volatility spillovers between financial markets in depth, the causality between markets is examined by using a recent causality-in-variance test following the procedure proposed by Cheung and Ng (1996). The causality-in-variance test assesses the conditional volatility dependence between two markets. However, traditional Granger causality test focuses on the mean changes. Causality-in-variance tests are able to identify the direction of causality as well as the number of leads/lags involved.

In the second part, we use the prices of six non-ferrous metals (aluminum, copper, lead, nickel, tin and zinc) and the price of crude oil to examine the dynamic links between oil and metal returns. We employ daily data for the period December 12, 2003 – December 15, 2008 and model the volatility process via the BEKK specification of the multivariate GARCH model. Then, cross-correlation function of the standardized residuals from the bivariate GARCH model of a pair of series under consideration form the basis of Cheung and Ng's (1996) measure of pair-wise causality tests. We realized that our results seem to be in line with the previous studies in that the crude oil market volatility leads all non-ferrous metal markets.

In the second chapter of our thesis, in our first part, we will model the six non-ferrous metals' prices using nonlinear autoregressive conditional heteroscedasticity models. In our second part, which is given in the third chapter, we use the six non-ferrous metals' prices and oil price to examine the causal relationships between each non-ferrous metal and oil prices by using bivariate nonlinear autoregressive conditional heteroscedasticity models.

CHAPTER II

FORECASTING THE PRICES OF NON-FERROUS METALS WITH GARCH MODELS

2.1. Introduction

Commodity markets are viewed as an alternative investment area by global investors. Investors are closely watching the developments in the global commodity markets as well as financial markets. Therefore, trade in commodity markets is probably following similar dynamics as in the global financial markets. The financial asset prices usually have time varying variance and investors frequently need to forecast the volatility processes in these markets. The fact that commodity markets are also used for hedging and speculation reasons has increased the need for modeling the volatility and forecasting the prices in these markets.

The commodity markets that attract the interest of global investors range from various agricultural products (including varieties of food and agricultural raw materials) and energy resources (coal, oil, natural gas etc.) to all kinds of metals (precious, ferrous and non-ferrous metals). There are a large number of studies on return spillovers and volatility forecasting of agricultural commodities, energy resources and metals. The profits of firms that use these commodities as inputs and that mine and trade these commodities are also significantly affected by the volatility in their prices. For example, the riskiness of a mining project can be assessed by not only risks involved in reserve estimation but also the future prices of the metal in concern. Hence, it is important to be able to forecast the commodity prices accurately (Dooley and Lenihan, 2005).

From a financial investment point of view, Chou (1988) states the importance of commodity volatility forecasts in valuation, portfolio formation, managing risk, and determining optimum options and futures trading strategies for hedging purposes. McMillan and Speight (2001) argue that the speculative activity has shown a shift from financial markets towards commodity markets, particularly to the non-ferrous metals market. They also point out that volatility forecasts become increasingly important for options pricing. It is also argued that the metal markets are good indicators of macroeconomic dynamics (Sari, Hammoudeh, & Ewing, 2007). Therefore, volatility forecasts may benefit policy makers as well as traders. Although ferrous and precious metals are recently receiving increasing attention from scholars, the literature on volatility forecasting of non-ferrous metal prices is relatively sparse. Non-ferrous metals are not only price sensitive to worldwide business cycles, but they are also sensitive to global energy markets.

Economic time series, particularly financial time series, exhibit periods of high volatility followed by periods of low volatility, which means the constant variance assumption is violated. The most appropriate method to deal with this violation is the use of GARCH models. The non-linear models have been the most commonly used tools in modeling and forecasting volatility of returns in the short run, but they may fail to capture the long run dynamics (McMillan and Speight, 2001). The primary aim of this study is to compare the forecast performances of three different generalized autoregressive conditional heteroscedasticity (GARCH) models regarding non-ferrous metal market returns.

The contributions of the part can be summarized as follows. First, we focus on returns of six non-ferrous metals that are traded in London Metal Exchange (LME). To the extent of our knowledge, the future returns and volatility processes of these six metals have not been studied together, applying the same models for comparison purposes. Second, we employ daily data instead of lower frequencies. In the literature, most studies use low frequency data (monthly and even quarterly), except for McMillan and Speight (2001); however, trade occurs more frequently and daily data may capture the dynamics more effectively. Third, we compare the forecasting performances of three different GARCH models. In the literature, usually different prices are evaluated using a single model. Therefore, to the extent of our knowledge this study is the first that studies the daily three-month average future prices of aluminum, copper, lead, nickel, tin, and zinc using three different GARCH models. We find that the forecasting performances of all three models are similar. However, we suggest the use of the GARCH model because it is more parsimonious and has a slightly better statistical performance than the other two.

This part is organized as follows. The next section gives a review of the literature, which briefly describes the previous GARCH applications and literature related to metal price forecasting. Section 3 presents the data and methodology used. Section 4 provides the empirical results of the study and concluding remarks are presented in the last section.

2.2. Literature Review

We divide the relevant research into two major areas, which are mainly volatility modeling and metal price forecasting. In a recent study, Engle (2004) provides historical details related to the development of conditional heteroscedasticity models and their evolution into more generalized models. According to Engle (2004), the GARCH (1,1) model has become "the workhorse of financial applications" when describing volatility dynamics. In the next section we briefly review some of the volatility models, and then we turn our attention to applications in metal price forecasting.

2.2.1. Volatility Modeling

Engle (1982) first introduces the ARCH models, and then Bollerslev (1986) and Taylor (1986) generalize these models to allow for conditional variance to depend on its own lags. Since then there has been a number of different models and estimation approaches that are primarily based on the GARCH model.

Nelson (1991) presents a class of ARCH models that are the "asymmetric" or "leverage" volatility models, in which future volatility can be affected differently by good news and bad news. These models do not suffer from some of the drawbacks of GARCH models like the negative correlation that exist between current returns and future returns volatility. GARCH models rule this out by assumption. Additionally, interpreting whether shocks to conditional variance "persist" or not is difficult in the GARCH models. The empirical work of French, et al. (1987) inspires a motivation for these models by finding the evidence that stock market returns are negatively correlated to the change in the volatility of stock returns.

Hamao, Masulis and Ng (1990) use daily opening and closing prices of major stock indexes for the Tokyo, London, and New York stock markets to examine the existence of price change and price volatility effects from one international stock market to the next. In order to explore these pricing relationships an ARCH family of statistical models is utilized in the analysis. They find that these relationships should be approximated by a GARCH (1,1)-M model. Evidence of price volatility spillovers from New York to Tokyo, London to Tokyo, and New York to London is observed but no price volatility spillover effects in other directions are found.

Engle and Ng (1993) make a systematic comparison of volatility models while focusing on the asymmetric effect of news on volatility. They propose volatility models and fitted these to daily Japanese stock returns from 1980 to 1988. All the models point out that negative shocks show more volatility than positive shocks but the diagnostic tests indicates that the modeled asymmetry is not sufficient. The asymmetric GARCH model which is proposed by Glosten et al. (1993) and the partially nonparametric (PNP) ARCH model give similar volatility forecasts for reasonable shock. However, these forecasts differ dramatically for more extreme shocks.

A modification of the classical ARCH models introduced by Engle (1982) is considered by Zakoian (1994). In this modified model the conditional standard deviation is a piecewise linear function of past values of the white noise. This specific form allows different reactions of the volatility to different signs of the lagged errors. Stationarity conditions are derived, maximum likelihood and least squares estimations are also considered.

In the paper of Lin, Engle and Ito (1994) how returns and volatilities of stock indices are correlated between Tokyo and New York are investigated empirically. In order to determine the global factor from daytime returns, they propose and estimate a signal extraction model with GARCH processes. They also investigate lagged return, volatility spillovers and several competing hypotheses regarding lagged spillovers in both returns and volatility are also tested. There are no significant lagged spillovers in returns or in volatilities, except for a lagged return spillover from New York to Tokyo for the period after the October 87 Crash. Moreover, they find some evidence of the lagged return spillovers from New York daytime to Tokyo daytime in the period after the Crash. On the other hand, they also find that, in general, there is no volatility spillover from one market to the other several hours later.

Morana (2001) uses the GARCH properties of oil price changes to forecast the oil price distribution over short-term horizons. The semi parametric forecasting methodology is based on the bootstrap approach. Morana (2001) suggests the use of the semi-parametric approach to construct a performance measure of the forward oil price using Brent oil prices. The semi-parametric methodology is suggested for the oil price forecasts as well.

Radha and Thenmozhi (2002) develop a univariate model for forecasting the short-term interest rates. The models under study are Random Walk, ARIMA, ARMA-GARCH and ARMA-EGARCH. According to the results of this study, volatility clustering effect is dominant in interest rates time series. As a result of this GARCH based models are more appropriate for forecast than the other models.

The moment structure of the general ARMA–EGARCH model is considered by Karanasos and Kim (2003). They show the differences in the moment structure between the EGARCH model with the standard GARCH model or the APARCH model and use these differences for comparison. They find that the autocorrelations of the squared observations can be applied so that the properties of the observed data can be compared with the theoretical properties of the models.

Bowden and Payne (2008) utilize three models, ARIMA, ARIMA-EGARCH, and ARIMA-EGARCH-M models to examine the day-ahead forecasting performance for hourly electricity prices for the five hubs of the Midwest Independent System Operator (MISO). The models do not differ significantly regarding their in-sample forecasting performances. However, with respect to the model performance in out-of sample forecasting, they find that the ARIMA-EGARCH-M model is superior to the other models.

Agnolucci (2009) compares the predictive ability of GARCH-type models and implied volatility models. His aim is to select the best model which produces the best forecast of volatility for the WTI future contracts and the evaluation criteria is based on statistics and regression results. He also investigates whether the asymmetric effects have an influence on volatility of the oil futures and whether the distribution of the errors affects the parameters of the GARCH models. According to the results of predictive ability tests, GARCH-type models seem to outperform the implied volatility (IV) model.

Allen and Morzuch (2006) provide a good summary of the past twenty five years of econometric forecasting and argue that ARCH has made significant contributions to the financial econometrics forecasting.

2.2.2. Forecasting Metal Prices

In the light of the brief discussion of volatility models, it does not come as a surprise to see that most of the applied work in metal price forecasting and volatility relies on GARCH models.

McKenzie, et. al (2001) investigate a range of commodity futures prices traded on the London Metals Exchange. They consider the ability of the Power GARCH models to capture the some features of volatility in these prices. The results of this study show that the LME futures data generally do not contain asymmetric effects. This paper suggests that the Taylor GARCH model outperforms other models included in the study.

Dooley and Lenihan (2005) analyze the ability of two time series forecasting techniques to predict global future lead and zinc prices. The time series methods that are used in the study are ARIMA and lagged forward price models. They argue that price forecasting is difficult. The results from their analysis suggest that ARIMA modeling provide better forecasts than lagged forward price modeling. They also claim that the models discussed in the study are widely used for base metal forecasting by the metal companies.

Hammoudeh and Yuan (2008) utilize three “two factor” volatility models of the GARCH family to examine the volatility behavior of three strategic commodities: gold, silver and copper, in the presence of crude oil and interest rate shocks. The results of the standard GARCH models suggest that gold and silver have almost the same volatility persistence which is greater than that of copper. The results of CGARCH and EGARCH procedures suggest that metals can have different volatilities because of their own special factors and uses, but not only driven by crises and common macroeconomic factors.

Figuerola-Ferretti and Gilbert (2008) apply the bivariate FIGARCH model to aluminum and copper prices, which are the two most important metals, traded in the London Metal Exchange. This model allows parsimonious representation of long memory volatility processes. The results show that aluminum and copper volatilities can be represented as long memory processes, in which the processes are symmetric and a common degree of fractional integration is exhibited by both of the metals.

The review of literature shows that ARCH and GARCH models are extensively used in price forecasting. However, there exist very few researches which apply the ARCH-GARCH family to futures prices of commonly traded non-ferrous metals. The literature shows that GARCH models are very successful at capturing the volatility clustering effect of financial time series and they usually outperform the ARIMA type models in capturing asymmetric effects and volatility clustering. Thus, this study focuses on forecasting of price volatilities non-ferrous metals traded in the London Metal Exchange using several non-linear models.

2.3. Data & Methodology

2.3.1. Data

Daily time series for the mean three-month futures prices of three commonly traded non-ferrous metals (aluminum, copper, lead, nickel, tin, and zinc) are used for this study. The sample covers the period December 12, 2003 – December 15, 2008. All three-month futures prices are sourced from London Metal Exchange (LME) and these prices are given in US dollars per ton. Dooley and Lenihan (2005) argue that the LME prices are generated by the most transparent pricing mechanisms resembling a perfectly competitive market. Hence, the market determines prices in LME can be used for hedging purposes which makes accurate price forecasts necessary. The total observations for each metal are 1305. All data used is in logarithmic returns. We first check the stationarity of the returns, and then utilize three different GARCH models for forecasting purposes. The last thirty days data are kept as the hold out sample and estimate the models with the remaining data set. Then the forecasting accuracy of the models is evaluated using the holdout sample.

2.3.2. Time Series Properties of the Data

The ARCH type modeling requires that the series under study be stationary. Therefore the first part of the analysis focused on the unit root properties of the return series. Several tests are available for testing the existence of unit roots, but the results are sometimes conflicting. In order to continue with the analysis safely, the stationarity of the series must be ensured. In theory, a time series is considered to be stationary if the series fluctuates around a constant mean which implies that the series have a finite variance. On the contrary, if a time series have a unit root this means the process is non-stationary. Namely, the series do not have a constant variance and no tendency to return to the predetermined path.

The commonly used methods in the literature to test for the presence of unit roots are augmented Dickey–Fuller (ADF) test belongs to, as the name implies, Dickey and Fuller (1979), Phillips–Perron (PP) developed by Phillips and Perron (1988), Elliot–Rothenberg–Stock Dickey–Fuller GLS detrended (DF–GLS) test proposed by Elliott, Rothenberg, and Stock (1996), a more comprehensive Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test is presented by Kwiatkowski, Phillips, Schmidt, and Shin (1992), Elliott, Rothenberg, and Stock (1996) developed a more recent test which is Elliott-Rothenberg-Stock (ERS) test and, Ng–Perron MZα (NP) test is created by Ng and Perron (2001). All of these procedures are applied so that the results of the study are more reliable. Detailed explanations of each of these procedures are not given here due to space limitations. However, extensive researches of Maddala and Kim (1998) and Ng and Perron (2001) can be used for detailed information about unit root tests.

In general, the ADF and PP tests are criticized because they have very low power; these tests cannot differentiate highly persistent stationary processes from non-stationary processes and the power of these tests diminish as deterministic terms are added to the test regressions. KPSS also has the same low power problems. Efficient unit root tests are proposed for maximum power by Elliot, Rothenberg, and Stock (1996) and Ng and Perron (2001). These tests have considerably higher power than the ADF, PP or KPSS unit root tests. All of these tests are included in this study because they are still in use in literature. Null hypothesis of all unit root tests employed in this study states that the series under analysis has a unit root (non-stationary) against the alternative that it is stationary. The only exception is the KPSS where the null hypothesis states that the series is stationary.

2.3.3. ARMA (p,q) – EGARCH (1,1)

The most common of the several asymmetric GARCH specifications is the EGARCH model, which is argued to be superior to alternative models (Radha & Thenmozhi, 2002). In order to carry out the analysis of metal price data, a form for the variance equation must be selected. The GARCH (1,1) specification for the variance equation is suggested in the literature for modeling volatility, so the EGARCH (1,1) model will be used in this study. The reason for that is the GARCH models do not take into account the leverage effect and hence the EGARCH model is used to capture whether the asymmetric effect is present. Proposed method of exponential GARCH or EGARCH model to capture the leverage or asymmetric effects by Nelson (1991) includes a coefficient, γ, which account for such asymmetries, as seen in the variance equation in equation (2.1):

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \tag{2.1}$$

Therefore, this variance equation follows the mean equation that is assumed to follow an ARMA (p,q) model. In this study, we select the best ARMA specification (p and q) based on Akaike Information Criterion (AIC). The ARMA model in general form is represented in equation (2.2):

$$y_t = \mu + \sum_{i=1}^{p} \emptyset_i y_{t-i} + \sum_{i=1}^{q} \theta_i u_{t-i} + u_t \quad (2.2)$$

After ensuring stationarity of the series, the models are estimated by maximum likelihood estimation procedure and the best model with the appropriate AR and MA lengths are selected via the minimum Akaike information criterion (Bozdogan, 2000). Then the inverted roots of the final model are also checked the stationarity of the model.

Last step in selecting the best ARMA specification is done for each non-ferrous metal price by significance tests of coefficients of the AR and MA terms. Additionally, the leverage effect is tested via the coefficient, γ, added into equation that account for such asymmetries.

2.3.4. ARMA (p,q) – GARCH (1,1)

Bollerslev (1986) introduced the generalized autoregressive conditional heteroscedastic (GARCH) models which describes the dynamic changes in conditional variance are dependent upon previous own lags. Because of this reason, the GARCH model is a more parsimonious model than the ARCH model. The GARCH family is extensively surveyed by Bollerslev, Chou, and Kroner (1992). They believe that the GARCH model is a very effective tool for examining volatility. Since the variance is known at time (t-1) in this model, one-step-ahead forecasts are already available. Multi-step-ahead forecasts can be calculated by repeating same procedure infinitely. As it was mentioned earlier in this chapter, GARCH (1,1) model is selected for variance equation while modeling volatility. The variance equation is given in equation (2.3):

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (2.3)$$

As in the EGARCH process, the best ARMA (p,q) specification (see equation 2.2) must be selected for the mean equation. The best specification selection proceeds exactly the same with the best ARMA specification selection in the ARMA (p,q) – EGARCH (1,1) part of the study, except the leverage effect.

2.3.5. ARMA (p,q) – TGARCH (1,1)

In order to model the asymmetric volatility in the GARCH process, Glosten, Jagannathan and Runkle (1993) and Zakoian (1994) independently introduced The Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) model or Threshold GARCH (TGARCH) model. In this model, the relation between current volatility and lagged error term depends on the sign of lagged error. The difference between true value and estimated value is the error term. This means if the lagged error is negative, it would mean that bad news which increases volatility, and we can say that there is a leverage effect. However, if the sign of lagged error is positive, it would indicate good news. Therefore, the asymmetric volatility model, TGARCH, can measure the concept of leverage effect empirically. It was mentioned earlier in this study that the GARCH (1,1) specification for the variance equation is suggested in the literature for modeling volatility, so the TGARCH (1,1) model will be used in this part. The variance equation of the TGARCH (1,1) model in general form is represented in equation (2.4):

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \alpha\epsilon_{t-1}^2 + \gamma\epsilon_{t-1}^2 I_{t-1}^- \tag{2.4}$$

Where $I_{t-1}^- = 1$ if $\epsilon_t < 0$ and 0 otherwise. As in the EGARCH and GARCH processes, the best ARMA (p,q) specification (see equation 2.2) must be selected for the mean equation. The best specification selection proceeds exactly the same with the best ARMA specification selection in the ARMA (p,q) – EGARCH (1,1) and the ARMA (p,q) – GARCH (1,1) parts of the study.

2.3.6. Forecasting

The best specification selection is followed by the evaluation of the forecasting results of GARCH (1,1), EGARCH (1,1) and TGARCH (1,1) models. Several measures are used to carry out this comparison and these measures are calculated as follows:

$$Root\ Mean\ Squared\ Error\ (RMSE) = \sqrt{\sum_{t=T+1}^{T+h} (\hat{y}_t - y_t)^2 / h} \tag{2.5}$$

$$Mean\ Absolute\ Error\ (MAE) = \sum_{t=T+1}^{T+h} {|\hat{y}_t - y_t|}/{h} \tag{2.6}$$

$$Mean\ Absolute\ Percentage\ Error\ (MAPE) = \sum_{t=T+1}^{T+h} |\hat{y}_t - y_t / y_t| / h \tag{2.7}$$

$$Theil\ Inequality\ Coefficient = 1 - \left(\frac{\sqrt{\sum_{t=T+1}^{T+h} (\hat{y}_t - y_t)^2 / h}}{\sqrt{\sum_{t=T+1}^{T+h} \hat{y}_t^2 / h} + \sqrt{\sum_{t=T+1}^{T+h} y_t^2 / h}} \right) \tag{2.8}$$

The first two error statistics, RMSE and MAE, mainly based on the dependent variable scale. Forecasts of different models are compared by using these relative measures. The model with the lowest value of the error statistics will lead to a better forecasting performance. The other two statistics do not depend on a relative scale. MAPE equals to 0 when explaining a perfect fit. However, MAPE does not have an upper restriction. The Theil inequality coefficient always gives values between zero and one, where perfect fit indicated by zero.

2.4. Empirical Results

Summary of the results of the unit root tests are given in Table (2.1). ADF, DF–GLS, and PP critical values are sourced from MacKinnon (1991). KPSS critical values are from Kwiatkowski, Phillips, Schmidt, and Shin (1992) and MZα critical values are from Ng and Perron (2001). Elliot, Rothenberg, and Stock (1996) gives the critical values of ERS. Although the results seems to maintain a conflict between the tests, in general the aluminum, copper, lead, nickel, tin, and zinc prices are stationary in levels which means that they are stationary in levels.

Table 2.1 - Unit root test results

	LEVEL	ADF	DF–GLS	PP	KPSS	ERS	NP (MZα)
Intercept	LPALUM	-37.93146[a] (0)	-8.462779[a] (7)	-37.93148[a] (1)	0.730881[b] (1)	0.117576 (0)	-60.7828[a] (7)
	LPCOPP	-39.77678[a] (0)	-3.008679[a] (11)	-39.65863[a] (9)	1.007609[a] (7)	0.103740 (0)	-5.19327 (11)
	LPLEAD	-35.06245[a] (0)	-2.019194[b] (18)	-35.08604[a] (3)	0.468279[b] (4)	0.071697 (0)	-3.58724 (18)
	LPNICK	-36.83380[a] (0)	-1.935740[c] (10)	-36.83006[a] (8)	0.486622[b] (8)	0.190515 (0)	-4.40567 (10)
	LPTIN	-35.02973[a] (0)	-4.850927[a] (9)	-35.01093[a] (5)	0.228858 (4)	0.111333 (0)	-18.8587[a] (9)
	LPZINC	-37.39598[a] (0)	-8.783922[a] (7)	-37.39501[a] (2)	0.965631 (4)	0.061405 (0)	-70.8203[a] (7)
Trend & Intercept	LPALUM	-38.10719[a] (0)	-7.882113[a] (7)	-38.10845[a] (4)	0.211725[b] (6)	0.233878 (0)	-52.1181[a] (7)
	LPCOPP	-40.03118[a] (0)	-5.152675[a] (11)	-40.04963[a] (6)	0.235424[a] (2)	0.186908 (0)	-13.3098 (11)
	LPLEAD	-35.14776[a] (0)	-20.96489[a] (1)	-35.14776[a] (0)	0.219265[a] (1)	0.156521 (0)	-494.132[a] (1)
	LPNICK	-36.90949[a] (0)	-3.692934[a] (10)	-36.90045[a] (7)	0.202120 (7)	0.227075 (0)	-15.1391[c] (10)
	LPTIN	-35.05110[a] (0)	-6.727110[a] (9)	-35.03616[a] (6)	0.183636[b] (5)	0.201831 (0)	-36.8733[a] (9)
	LPZINC	-37.59474[a] (0)	-36.36479[a] (0)	-37.60362[a] (6)	0.214173[b] (8)	0.159675 (0)	-651.455[a] (0)

Notes to table: Numbers in parentheses are the lag lengths. [a, b, c] Significant at 1%, 5%, and 10% levels, respectively. All of the null hypotheses are unit root, except KPSS; however, in KPSS the null is stationarity.

Stationarity of the series is tested so that it is understood that they do not contain unit roots as can be observed from Table (2.1). According to the test results with different specifications the series employed do not contain unit roots. Literature suggests that the presence of autoregressive conditional heteroscedasticity in the residuals raises the possibility of the leverage effect. In order to examine the possibility of the leverage effect, an ARMA-EGARCH (1,1) model is estimated. The ARMA models of order up to (1,1) for the natural logs of six metal prices are estimated. The Akaike information criterion (AIC) (not reported here) choose ARMA(1,0) specification for the prices for aluminum and copper, ARMA(0,1) specification for lead and nickel prices. For tin and zinc, ARMA (1,1) specification minimizes the Akaike Information Criterion. In addition, t-statistics of coefficient estimates are used to evaluate the performance of the selected specifications. The tests (not reported here) show that ARMA(1,0) specification is statistically appropriate for the prices for aluminum and copper, selected specification of ARMA (0,1) is suitable for lead and nickel. Identically, the results for t-statistics ARMA (1,1) specification are appropriate for tin and zinc. The mean equations are checked for ARCH effects and all are found to be significant.

For all the metal prices, parameter estimation is conducted similarly on an EGARCH (1,1) for variance equation and the appropriate ARMA model for the mean equation. Best specifications for aluminum and copper prices is ARMA(1,0)-EGARCH(1,1), ARMA(0,1)-EGARCH(1,1) for lead and nickel prices and ARMA(1,1)-EGARCH(1,1) for prices of tin and zinc.

Proposed method of exponential GARCH or EGARCH model to capture the leverage or asymmetric effects is Nelson’s (1991) which includes a coefficient that account for such asymmetries. The interpretation of this coefficient in the variance equation of the EGARCH model shows that asymmetric effect is not present in prices of the six commonly traded non-ferrous metals and it is statistically insignificant (as seen in table 2.2) . Note that all coefficients, except the asymmetric effect coefficient and the constant term in the tin equation, are statistically significant. Some diagnostic statistics are also reported that show non existence of serial correlation but evidence of non-normality in the residuals of all six nonferrous metal price volatility equations. The diagnostic test statistics are reported below the estimation results.

The best ARMA specification selection for the GARCH models proceeds exactly the same with the best ARMA specification selection in the ARMA (p,q) – EGARCH (1,1) part of the study, except the leverage effect part. Best specifications for aluminum, copper, lead, and nickel prices is ARMA(0,1)-GARCH(1,1), ARMA(1,1)-GARCH(1,1) for the prices of tin, and ARMA(0,0)-GARCH(1,1) for zinc prices. Results for the GARCH model are summarized in Table (2.3). Note that for all six prices all coefficients, except the constant in nickel equation, are significant. There is no serial correlation problem according to the Q statistics, but the residuals are non-normal.

Table 2.2 - EGARCH Results

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \quad (2.1)$$

Equation for variance specification	EGARCH (2.1)					
	LPALUM	LPCOPP	LPLEAD	LPNICK	LPTIN	LPZINC
ω	-0.079426[a]	-0.083540[a]	-0.067916[a]	-0.052077[b]	-0.071993	-0.081076[a]
	(0.026762)	(0.028723)	(0.025365)	(0.022860)	(0.065914)	(0.027850)
β	0.976429[a]	0.976574[a]	0.980477[a]	0.986982[a]	0.854087[a]	0.971787[a]
	(0.008434)	(0.010879)	(0.009883)	(0.008950)	(0.054269)	(0.009974)
γ	0.043081	-0.003261	0.002387	-0.003855	-0.051733	0.003219
	(0.028731)	(0.028650)	(0.021854)	(0.018948)	(0.054584)	(0.026896)
α	0.132326[a]	0.156935[a]	0.133245[a]	0.103187[a]	0.360663[a]	0.166648[a]
	(0.036731)	(0.046162)	(0.031605)	(0.034227)	(0.082024)	(0.044247)
ARCH LM (1)	0.131432	0.618113	0.597915	0.096236	1.228127	3.61E-06
Q (10)	6.0892	7.8296	10.629	10.924	12.392	7.7276
Q^2 (10)	2.0562	3.1503	8.0084	10.039	6.1296	5.2989
JB	670.4308[a]	837.7862[a]	151.6183[a]	231.5599[a]	996.8076[a]	215.1491[a]

Notes to Table: Coefficient estimates and their standard errors are given in parentheses. The ARCH LM test is commonly used to test for the existence of ARCH. The null hypothesis is that there is no ARCH up to 1 order in the residuals. The Q (10) and Q^2 (10) statistics are a test statistic for the null hypothesis that there is no autocorrelation up to order 10. Jarque-Bera(JB) is used for testing whether the series is normally distributed. [a, b, c] Significant at 1%, 5%, and 10% levels, respectively.

The TGARCH results are summarized in Table (2.4). Exactly the same selection process is applied to the best ARMA specification selection for the ARMA (p,q) – EGARCH (1,1) part of the study. ARMA (0,1)-TGARCH (1,1) specification is selected for aluminum, copper, lead, nickel, and zinc. On the other hand, ARMA (1,1)-TGARCH (1,1) specification is selected for tin prices. The coefficient of the threshold dummy is significant only for the aluminum equation. Note that all other coefficients are statistically meaningful. The TGARCH model also does not suffer from the autocorrelation problem, but non-normality is evident according to the Jarque-Bera test statistics.

Table 2.3 - GARCH Results

$$\sigma_t^2 = \omega + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{2.3}$$

Equation for variance specification	GARCH (2.3)					
	LPALUM	LPCOPP	LPLEAD	LPNICK	LPTIN	LPZINC
ω	0.067692[a]	0.127234[c]	0.106122[c]	0.110540	0.363186[b]	0.095307[a]
	(0.024939)	(0.070972)	(0.056818)	(0.074460)	(0.143999)	(0.036169)
β	0.904395[a]	0.892974[a]	0.908119[a]	0.933768[a]	0.758120[a]	0.910125[a]
	(0.022494)	(0.035641)	(0.022842)	(0.022429)	(0.061834)	(0.021346)
α_1	0.067203[a]	0.078360[a]	0.076236[a]	0.052189[a]	0.157721[a]	0.074418[a]
	(0.027845)	(0.026566)	(0.017695)	(0.017181)	(0.042958)	(0.019853)
ARCH LM (1)	0.002985	1.000002	0.227270	0.147502	1.142385	0.023253
Q (10)	5.2046	8.1292	9.7672	10.942	6.0128	7.1983
Q^2 (10)	2.2317	3.8028	5.8067	8.8265	6.8074	4.6377
JB	933.4370[a]	776.3191[a]	104.9789[a]	239.6559[a]	1106.801[a]	264.2795[a]

Notes to Table: Coefficient estimates and their standard errors are given in parentheses. The ARCH LM test is commonly used to test for the existence of ARCH. The null hypothesis is that there is no ARCH up to 1 order in the residuals. The Q (10) and Q^2 (10) statistics are a test statistic for the null hypothesis that there is no autocorrelation up to order 10. Jarque-Bera(JB) is used for testing whether the series is normally distributed. [a, b, c] Significant at 1%, 5%, and 10% levels, respectively.

After the best specification selection for all three models across six metal prices, we continue with the evaluation of the forecasting results of the selected models. Based on the RMSE and MAE performance measures in Tables (2.5), (2.6) and (2.7), GARCH (1,1) models are slightly superior to EGARCH (1,1) and TGARCH (1,1) models for lead, nickel, and zinc prices. On the contrary, TGARCH (1,1) models are slightly superior to GARCH (1,1) and EGARCH (1,1) models for the prices of copper. Moreover, EGARCH (1,1) model gives the best results among all of three models for the prices of tin. However, one should also remember that the asymmetric effect coefficients in these models are both insignificant.

Table 2.4 - TGARCH Results

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \alpha\epsilon_{t-1}^2 + \gamma\epsilon_{t-1}^2 I_{t-1}^- \quad (2.4)$$

Equation for variance specification	TGARCH (2.4)					
	LPALUM	LPCOPP	LPLEAD	LPNICK	LPTIN	LPZINC
ω	0.038165[a]	0.120301[c]	0.088879[c]	0.107428	0.432439[a]	0.076209[b]
	(0.013858)	(0.067481)	(0.053258)	(0.073826)	(0.162062)	(0.030341)
β	0.919714[a]	0.898546[a]	0.915094[a]	0.934275[a]	0.728974[a]	0.919886[a]
	(0.017411)	(0.035499)	(0.021898)	(0.022255)	(0.069925)	(0.020317)
γ	-0.066756[c]	0.001037	-0.013496	-0.004446	0.085020	-0.022893
	(0.038974)	(0.039386)	(0.027498)	(0.028711)	(0.087689)	(0.033575)
α	0.103946[a]	0.073639[c]	0.079685[a]	0.054474[b]	0.124323[c]	0.081126[b]
	(0.031908)	(0.038227)	(0.026962)	(0.027055)	(0.067000)	(0.033583)
ARCH LM (1)	0.000822	0.903491	0.336187	0.149492	0.787501	0.000829
Q (10)	5.6734	8.2721	9.7590	11.031	6.0691	7.5620
Q^2 (10)	1.7591	3.6499	5.8695	8.6216	6.4211	4.0504
JB	642.1407[a]	791.0539[a]	108.2352[a]	234.6295[a]	1014.128[a]	276.9781[a]

Notes to Table: Coefficient estimates and their standard errors are given in parentheses. The ARCH LM test is commonly used to test for the existence of ARCH. The null hypothesis is that there is no ARCH up to 1 order in the residuals. The Q (10) and Q^2 (10) statistics are a test statistic for the null hypothesis that there is no autocorrelation up to order 10. Jarque-Bera(JB) is used for testing whether the series is normally distributed. [a, b, c] Significant at 1%, 5%, and 10% levels, respectively.

Also the interpretation of MAPE results confirms the RMSE and MAE results (see Tables (2.5), (2.6) and (2.7),) that GARCH (1,1) model results in a slightly better fit than EGARCH (1,1) models for aluminum, lead, nickel, and zinc data. TGARCH (1,1) model gives better results than EGARCH (1,1) and GARCH (1,1) models for copper prices and EGARCH (1,1) gives a slightly better fit than GARCH (1,1) and TGARCH (1,1) for tin prices when we look at the RMSE, MAE and MAPE results. However, Theil inequality coefficient gives slightly conflicting results with other three forecasting error statistics for all six data sets. Namely, according to Theil inequality coefficient estimates TGARCH (1,1) model result in a better fit than EGARCH (1,1) and GARCH (1,1) models for aluminum, lead, nickel, and zinc data sets and GARCH (1,1) model result in a better fit than EGARCH (1,1) and TGARCH (1,1) models for copper and tin data sets (see Tables (2.5), (2.6) and

(2.7)). Regardless of the model used, best forecast results are observed for tin among the six metals studied.

Table 2.5 - EGARCH Forecast Statistics

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \quad (2.1)$$

Equation for variance specification	EGARCH (2.1) LPALUM	LPCOPP	LPLEAD	LPNICK	LPTIN	LPZINC
RMSE	1.457008	2.068801	2.400428	2.639875	1.974897	2.251417
MAE	1.060954	1.436628	1.752658	1.914785	1.346196	1.633354
MAPE	0.954044	1.008427	0.93979	0.949081	0.904089	0.958337
TIC	0.029662	0.040594	0.050179	0.00598	0.026662	0.047784

Table 2.6 - GARCH Forecast Statistics

$$\sigma_t^2 = \omega + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (2.3)$$

Equation for variance specification	GARCH (2.3) LPALUM	LPCOPP	LPLEAD	LPNICK	LPTIN	LPZINC
RMSE	1.456375	2.068339	2.400340	2.639791	1.991592	2.249464
MAE	1.059823	1.436630	1.752576	1.913982	1.365957	1.631546
MAPE	0.947852	1.005874	0.938925	0.945501	0.947722	0.94753
TIC	0.005611	0.039218	0.048909	0.000668	0.09114	0.034492

Table 2.7 - TGARCH Forecast Statistics

$$\sigma_t^2 = \omega + \beta \sigma_{t-1}^2 + \alpha \epsilon_{t-1}^2 + \gamma \epsilon_{t-1}^2 I_{t-1}^- \quad (2.4)$$

Equation for variance specification	TGARCH (2.4) LPALUM	LPCOPP	LPLEAD	LPNICK	LPTIN	LPZINC
RMSE	1.456373	2.068321	2.400465	2.639804	1.992378	2.249785
MAE	1.060286	1.436610	1.752690	1.914169	1.366440	1.631868
MAPE	0.951904	1.004915	0.940132	0.946334	0.946178	0.950101
TIC	0.023491	0.038708	0.05068	0.001911	0.089828	0.038328

2.5. Summary and Conclusions

In this study the six non-ferrous metals' prices are modeled using nonlinear autoregressive conditional heteroscedasticity models. We discover that the six prices are governed by the conditional heteroscedasticity effects. Therefore, appropriate models for these prices can be found within the GARCH family. We utilize the GARCH, TGARCH and EGARCH models for all six prices in this research. Then we compare the forecasting accuracy of the three models according to several statistical criteria. We find that in general all three models show similar performance in forecasting the prices of the six metals. However, the GARCH model performs slightly better than the EGARCH and TGARCH models according to several criteria for lead, nickel, and zinc metals. The MAE and MAPE choose the GARCH model, whereas the RMSE and TIC choose the TGARCH model for aluminum prices. For tin prices, the EGARCH model outperforms the GARCH and TGARCH models according to several criteria. As for the copper prices, TGARCH seems to be the most appropriate model. Since the GARCH model is more parsimonious and the asymmetric effect coefficients in TGARCH and EGARCH models are insignificant, we recommend the utilization of the GARCH model for forecasting the prices of all six metal prices. The similar performances of the three models with respect to statistical criteria do not necessarily imply that one of them will outperform the others in practice. Therefore, further research would be beneficial in understanding whether investors may profitably benefit from improved forecast accuracy depending on several trading strategies.

CHAPTER III

VOLATILITY SPILLOVER FROM WORLD OIL MARKET TO NON-FERROUS METAL MARKETS

3.1. Introduction

Changes in the oil price affect most sectors of most economies at various degrees. Recent research has shown that commodity prices of all kinds rise and fall in unison. Crude oil prices affect the prices of other commodities in a number of ways. Such co-movements are typically attributed to common macroeconomic shocks on world commodity markets, and complementarity or substitutability in the production or consumption of related commodities. For instance, some metals such as aluminum have to go through an energy-intensive primary processing stage. Pindyck and Rotemberg (1990) find that the prices of a group of unrelated commodities had a tendency to move together, even after accounting for the effects of common macroeconomic variables. This co-movement and its explanations may be more relevant to strategic commodities such as oil, gold, silver and copper which have varying but important degrees of industrial usages and influences. This part focuses on the pass-through of crude oil price changes to the prices of six internationally traded non-ferrous metals.

Policy makers are mostly concerned about the short run and the long run impacts of the recent rise and subsequent fall in world oil prices on the macroeconomy. On the other hand, main issues of the traders are that whether these impacts are permanent or temporary and how the non-ferrous metal returns will respond to oil shocks. Oil price changes are generally found to have significant effects both on the economy and financial markets. Several studies have examined the relationship between oil prices and commodity prices, but a small number of studies focus on the impact of oil shocks on non-ferrous markets, where academicians and practitioners alike have been trying to understand the dynamic links between world oil prices and non-ferrous metal returns.

The constant variance assumption is violated in financial time series, which means periods of high volatility followed by periods of low volatility. The multivariate GARCH models are the most appropriate method to deal with this violation. McMillan and Speight (2001) state that the non-linear models have been the most commonly used tools in modeling and forecasting volatility of returns in the short run, but they may fail to capture the long run dynamics. This study is related to the literature on the impact of oil price changes on commodity prices; however, it is differentiated from the rest of the literature by examining the impact of fluctuations of oil prices on non-ferrous metal returns as well as volatility spillovers. The stocks of companies operating in metal markets are more sensitive to world oil price changes.

In finance, there exists a wide area for the application of MGARCH models. An illustrative list of some typical applications can be given by introducing the model of the changing variance structure in an exchange rate regime (Bollerslev, 1990), the optimal debt portfolio calculation in multiple currencies (Kroner and Claessens, 1991), the multiperiod hedge ratios evaluation of currency futures (Lien and Luo, 1994), the international transmission examination of stock returns and volatility (Karolyi, 1995) and the optimal hedge ratio estimation for stock index futures (Park and Switzer, 1995). However, we employ a multivariate GARCH model to simultaneously estimate the appropriate residuals using daily returns from December 12, 2003 to December 15, 2008. Examination of temporal relationships through the creation of large models with many lags is allowed when the powerful time series techniques are introduced. In the literature the Granger causality tests are referred to interpret the results as well as impulse response and variance decomposition analyses, because of the problems in the interpretation of lagged variable coefficients. An example for the interpretation of results can be given as; if lags of a variable X improve the interpretation of another variable Y, then we can said that X

Granger causes Y. In the relevant literature of the oil price-commodity prices, everybody believes that fluctuations in oil price changes affect the prices of other commodities, but not vice versa, especially in minor commodity markets in relation to the vital commodity markets. This theoretical belief does not always match with the experimental results. Several reasons may exist ranging from the methodology related problems to the commodity market characteristics. Reason for the absence of a causal link between oil price and commodity prices is that there may be a dynamic link between the variables themselves as well as the variances of the variables. Hence, one should focus not only on mean, but also variance spillovers in order to fully examine the dynamic links between oil and metal returns.

The chapter is organized as follows. In the next section a brief review of literature that is related to the study is given. Section 3 discusses the data used in the study and the methodology applied in the study. Section 4 presents empirical results while section 5 concludes the chapter.

3.2. Literature Review

Here we first summarize GARCH models mainly used in modeling stock market prices and volatilities as well as currency markets. Then we review studies that focus on commodity prices, especially oil and metal prices. Please note that a bulk of the literature has been reviewed in the first part of the thesis, therefore we do not delve too deep into the literature in this part to avoid overlaps.

The survey paper of Bera and Higgins (1993) provide an account of some of the important developments in the autoregressive conditional heteroscedasticity (ARCH) model since it is introduced by Engle (1982) in his seminal paper. More and more features of the real world are accommodated by generalized ARCH models. A comprehensive treatment of many of the extensions of the original ARCH model is provided in this paper. Moreover, estimation and testing for ARCH models are discussed and note that these models lead to some interesting and unique problems.

Structural change, different kinds of nonlinearities, cointegration and finite sample properties of estimators and test statistics are the problems that being investigated. In this survey paper, they provide a brief account of these problems. The ARCH models offer a more adaptive framework for nonlinear dynamic characteristics problem of the financial time series than the classical ARMA models because of its limitations. Gourieroux (1997) survey the recent work in this area from the perspective of statistical theory, financial models, and applications and will be of interest to theorists and practitioners.

Bollerslev, Chou and Kroner (1992) survey several research papers on the methodology and applications of GARCH and MGARCH models that they consider to be the most important and promising in the formulation of ARCH-type models. This overview of the extensive ARCH literature serves as a catalyst in fostering further research in this important area. The basic framework for a multivariate generalized autoregressive conditional heteroscedasticity model is provided by Bollerslev, Engle and Wooldridge (1988). The univariate case of the GARCH representation is extended in to the vectorized conditional-variance matrix. They estimate a MGARCH process for returns to bills, bonds, and stocks where the expected return is proportional to the conditional covariance of each return with that of a fully diversified or market portfolio. The main result of their paper is that the conditional covariances are quite variable over time. Moreover, the implied betas are also time-varying and forecastable. Engle and Kroner (1995) extend Engle's (1982) ARCH model and Bollerslev's (1986) GARCH model to a multivariate setting by presenting theoretical results on the formulation and estimation of multivariate generalized ARCH models within simultaneous equations systems. For the sake of parameterization of the multivariate process, a new formulation is proposed (BEKK) and compared with the existing parameterization of the multivariate ARCH process, the (VECH). Bauwens, Laurent and Rombouts (2006) review the multivariate GARCH models which are increasingly used in applied financial econometrics. According to them, providing a realistic but parsimonious specification of the variance matrix ensuring its positivity is the crucial point in MGARCH modeling.

There is a trade-off between flexibility and parsimony. A lot of parameters are needed for flexible BEKK. On the other hand, restrictive diagonal VEC and BEKK models are much more parsimonious.

Another step forward in methodological development is allowing the conditional correlations to vary through time. The theoretical and empirical properties of Dynamic Conditional Correlation (DCC) Multivariate GARCH are developed by Engle and Sheppard (2001). S&P 500 Sector Indices and Dow Jones Industrial Average stocks are used to estimate the conditional covariance of up to 100 assets using and to conduct specification tests of the estimator using an industry standard benchmark for volatility models. However, we limit ourselves to MGARCH models and assume constant conditional correlations, so that our results are comparable to studies that employ the same methodology in different commodity markets.

In their article, King and Wadhwani (1990) investigate the outcome of rational attempts to use imperfect information about the events in order to examine a rational expectations price equilibrium and model contagion between markets. A contagion model is constructed to explain why all stock markets fell together despite widely differing economic circumstances. Market prices reveal all relevant information to agents in models of rational expectations equilibrium with asymmetric information, provided that there is a relatively simple information structure. They show that covariances are related to volatility with high-frequency data. An implication of this result is that an increase in volatility could be self-reinforcing and persist for longer than would otherwise be the case. As volatility declines, market links become weaker, and price changes are less closely tied together.

Bollerslev (1990) propose a simple multivariate conditional heteroscedastic time series model. The model has constant conditional correlations, but time varying conditional variances and covariances. The estimation and inference procedures are greatly simplified with the help of this structure. The parameterization proposed here with constant conditional correlations but time varying conditional covariances represents a major increase in terms of computational simplicity when compared to Bollerslev, Engle and Wooldridge (1988)'s the linear diagonal GARCH model, Diebold and Nerlove (1989)'s the latent factor ARCH model, or Engle, Ng, and Rothschild (1990)'s the factor GARCH model. Finally, the various ARCH and GARCH parameterizations suggested in the literature represent nothing but a convenient statistical tool for summarizing the time series dependence observed in the data.

A multivariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model is used to estimate a sequence of optimal dynamic hedging portfolios, since the model of Kroner and Claessens (1991) permits the second moments to change through time. Actual model shows that the currency composition of a country's external debt can serve as a hedging instrument against changes in exchange rates and commodity prices. They apply it to Indonesia to illustrate the usefulness of the technique. As expected, this application shows that Indonesia's optimal debt portfolio consists of a much larger proportion of US dollars and a much smaller proportion of Japanese yen than they have in their current debt portfolio.

In their article, Engle and Susmel (1993) investigate whether two international stock markets share the same volatility process by using the advantage of the time-varying structure of stock-returns variances. A recent test which is developed by Engle and Kozicki is used to assess the validity of a one-factor autoregressive conditional heteroscedasticity model. Main result of this paper is that some international stock markets have the same time-varying volatility.

Lien and Luo (1994) use a basic bivariate GARCH model for multiperiod hedge ratio estimates. The optimal multiperiod hedge ratio is derived prior to the introduction of conditional heteroscedasticity into the joint price process. An error correction model describes the mean process while the GARCH specification is applied to model the conditional heteroscedasticity. This model is applied, in order to empirically determine the hedge ratios major foreign exchange markets. For each case, GARCH hedge ratios perform a little better than three alternative hedge strategies (no hedge, constant hedge and error correction hedge).

Karolyi (1995) use a bivariate generalized autoregressive conditional heteroscedastic (GARCH) model to examine the dynamic relationship between daily stock-market returns and return volatilities of the U.S. and Canadian. Two tests are conducted with this model. First test is how rapidly stock-return innovations originating in the U.S. and Canadian markets transmit to the other market and second one is how rapidly the volatility of these innovations transmits to the other market by simulating the impulse responses of the estimated bivariate GARCH model. The relationships between stock-price movements in the U.S. and Canadian markets are confirmed by the test results which show that the bivariate GARCH model is a reasonable representation. More precisely, tests using multivariate GARCH models indicate that the effects of shocks are smaller and less persistent than those measured with traditional vector autoregressive (VAR) models.

Huang, Masulis and Stoll (1996) use a multivariate vector autoregressive (VAR) approach to examine the contemporaneous and lead-lag correlations between daily returns of oil futures contracts and stock returns which answer the general question of the information transmission mechanism linking oil futures with stock prices. One of the many possible scenarios is that the relevant information affecting each of these markets is informationally segmented from the other, oil futures prices and stock prices will be unrelated. Dynamic interactions among price changes of different financial instruments are easily examined by the highly flexible framework of the VAR representation. The conclusions from the VAR approach are oil futures returns are not correlated with stock market returns. In fact, the lack of correlation suggests that oil futures, like other futures contracts that also appear to have little correlation with stocks, are a good vehicle for diversifying stock portfolios (Huang, Masulis and Stoll, 1996).

A simple model of speculative trading is developed by Fleming, Kirby and Ostdiek (1998) to examine the nature of volatility linkages in an economy which is based on the relation between volatility and information flow in multiple securities markets. In speculative trading, traders' current expectations and risk tolerances influence the trader's positions in one or more futures contracts. Market linkages are generated in two ways by information under the model. First one is that the information is common across markets and second one is that there is an information spillover between markets). According to Fleming Kirby and Ostdiek (1998), "The model predicts strong volatility linkages in markets where the hedging benefits are large and the hedging costs are small. We use a stochastic volatility representation of the model to estimate the volatility linkages for three futures markets where we expect both common information and information spillover to be important: the stock, bond, and money markets."

Pan and Hsueh (1998) employ a two-step GARCH approach to examine the nature of transmission of stock returns and volatility between the U.S. and Japanese stock markets by using stock index futures prices on the S&P 500 and Nikkei 225 stock indexes in order to obtain more robust results. Results show that there are unidirectional contemporaneous return and volatility spillovers from the U.S. to Japan. Another interpretation of the results is that there are no significant lagged spillover effects in both returns and volatility from the Osaka market to the Chicago market, while a significant lagged volatility spillover is observed from the U.S. to Japan. Hafner and Herwartz (1998) use a multivariate GARCH framework to give empirical evidence of time-varying market price of risk for the German stock market. De Santis and Gerard (1998) use a parsimonious multivariate GARCH process to test the conditional version of an International Capital Asset Pricing Model (ICAPM). They find strong support for a specification of the ICAPM that includes both market risk and foreign exchange risk, assuming that the prices are allowed to change over time. Results show that if both the market and currency risk components are incorporated into the model, there will be no need to use the additional information variables to explain the cross-section and the dynamics of expected returns.

Sadorsky (1999) investigates the impact that oil price shocks may have on stock market returns by using monthly data. Results from a VAR suggest that changes in economic activity have little impact on oil prices but changes in oil prices impact economic activity and the results of impulse response functions suggest that positive shocks to oil prices depress real stock returns while shocks to real stock returns have positive impacts on interest rates and industrial production.

Kearney and Patton (2000) contribute to the MGARCH modeling and exchange rate volatility transmission literature by presenting a series of 3-, 4- and 5-variable multivariate GARCH models to examine how exchange rate volatility is transmitted with the EMS exchange rate system. They argue that alternative specifications should be examined to clarify the robustness of results.

Kim (2000) uses a multivariate GARCH-M model to analyze the relation of exchange rate volatility and output volatility. Source decomposition of observed volatility of output into domestic factors, foreign factors and exchange rate movements and also extraction of the expected volatility from the total volatility is easily accomplished by the multivariate GARCH-M modeling. According to the results, Japanese economy is insulated itself from foreign shocks with the help of the floating exchange rate regime.

Tse and Tsui (2000) adopt the VECH representation to propose a new MGARCH model with time-varying correlations. However, the conditional variances and conditional correlations are the variables of interest. Their new model satisfies the positive-definite condition as found in the constant-correlation and BEKK models while retaining the intuition and interpretation of the univariate GARCH model.

In addition to stock market and currency market applications, the GARCH models are also frequently used in the recent literature on commodity prices, especially the oil prices. The interest ranges from the link between different energy prices to oil spills to other commodity and financial markets.

There are several recent studies that analyze the dynamics of metal prices along with oil. For example, Sari et al. (2010), Soytas et al. (2009), and Hammoudeh et al. (2009) focus on the link between precious metals with various other variables, like oil price and the exchange rate. These studies put forth the importance of investigating the dynamics of metal prices. Since they do not focus on volatility transmissions we do not discuss them in too much detail here.

Ewing, Malik and Ozfidan (2002) use daily returns data to examine the transmission of volatility between the oil and natural gas sectors changes over time and across markets. . The univariate and bivariate time-series properties of oil and natural gas index returns are empirically examined by robust methodology in which the changes in volatility in one market may spill over to the other market is allowed and non-linearity in the variance of each series can easily be examined. Results of the study show that returns exhibit time-varying volatility which implies volatility in natural gas returns is more persistent than volatility in oil returns.

Hammoudeh, Dibooglu and Aleisa (2004) employ unit root tests, cointegration tests, error-correction models with day effects, and univariate and multivariate ARCH/GARCH models with day and oil spillover effects to examine the intra- and interlinks for two U.S. markets of oil prices and S&P oil sector stock indices. In this study, the multivariate GARCH model helps to capture simultaneous volatility interactions. Moreover, MGARCH model shows that the transmission of volatility between prices, something that was not revealed by the univariate GARCH model.

Bhar and Hamori (2005) use a recent econometric methodology to analyze causal relationship between crude oil futures return and the trading volume using daily data over a ten-year period. The two-step procedure developed by Cheung and Ng (1996) is used and they find only causality at higher order lags running from return to volume in the mean as well as in conditional variance. There exist several conflicts with earlier studies in this area. We utilize the same methodology in this study.

Eckner (2006) introduces a model for asset returns that incorporates joint heteroscedasticity as well as time varying correlations which is suitable for capturing the dynamics of multivariate return time series. The empirical results give an explanation why the volatility smile in index options tends to be more pronounced than in individual stocks options.

Malik and Hammoudeh (2007) estimate the mean and conditional variance of daily returns in the oil, US and Gulf equity markets at the same time by using the BEKK specification of the multivariate GARCH model. The main reason behind using the BEKK is that it does not impose the restriction of constant correlation among variables over time. They examine the volatility and shock transmission among US equity market, global crude oil market, and equity markets of major oil rich Gulf countries since shocks can spillover from one country to another. The results show significant volatility transmission among US equity market, global crude oil market, and equity markets of major oil rich Gulf countries. Additionally, these results are important for building accurate asset pricing models and forecasting future volatility in equity and oil markets.

Inagaki (2007) employ the residual cross-correlation approach to investigate volatility spillover between the British pound and the euro. They believe that the causality in variance approach is useful for analyzing exchange rates that often exhibit conditional heteroscedasticity. Since it does not involve simultaneous modeling which makes it is easier to implement than the multivariate method. Their findings suggest that the euro volatility has a one-sided impact on the British pound volatility and they conclude that the euro is the most influential European currency.

In the review paper of Silvennoinen and Terasvirta (2008) a number of multivariate GARCH models and its specifications are surveyed. Using the original VEC model is obviously very tedious because of too many parameters, so finding parsimonious alternatives is the main focus of this research. Two alternatives are generated. First, some restrictions are imposed on the parameters of the VEC model to create new models, such as the BEKK model and the factor models. Second, modeling conditional covariance through conditional variances and correlations is another idea. Several new models are generated, and conditional correlation model family seems to become quite popular.

In order to extract information for risk prediction Chow and Fung (2008) use a MGARCH structure to offer a quantitative approach to analyzing possible associations of stock price changes and variations in innovative activities. Results show that the model can pick up the correlation between the two variables and aid in producing accurate Value-at-Risk estimates. The statistical evidence is confirmed by the model comparison exercises which suggest that the assumption of MGARCH (1,1) is sufficient for this type of study.

3.3. Data & Methodology

3.3.1. Data

We use daily data on the mean three-month futures prices of six commonly traded non-ferrous metals (aluminum, copper, lead, nickel, tin, and zinc), and spot oil price for the period December 12, 2003 – December 15, 2008[1]. All three-month futures prices are sourced from London Metal Exchange (LME) and these prices are given in US dollars per ton. The "Dated Brent" Spot Price reflects the average price of "Brent-Forties-Oseberg-Ekofisk" (BFOE) cargoes loading 10-21 days forward and given in US dollars per barrel. The total observations for each data set are 1305. The natural logarithms of all data are arranged in 5 day weeks and all holidays are removed.

In non-ferrous metal markets, futures price is combination of spot price, interest and storage costs. In some sense, the futures price is above spot because by buying

[1] We have chosen the start date so as to move as far away from the effects of 9/11, this allowed us to retain more than 1300 observations.

forward the purchaser avoids the finance and storage cost. However, we use the spot oil prices instead of futures, since oil prices are very volatile. But much of this volatility seems to be reflected in short-term, transitory factors that may have little or no influence on the price in the long run. Moreover, consistent with the practice in the finance literature, there really is no "true" spot market for oil, in the sense of that there is a "true" spot market for stock or other financial assets. A "true" spot market requires the actual physical transfer of the goods, to the purchaser, directly at the time of purchase. When we refer to "futures" price for crude oil, it includes spot price, interest, storage costs and scarcity/prompt/convenience premium. In that case using spot oil price instead of futures is more convenient for our study.

3.3.2. Methodology

The first step in the procedure is assuring the stationarity of each price series by using the unit root tests. The unit root test procedures are already summarized in Chapter 2 of this thesis (see page 14). Then, the multivariate GARCH process is modeled to analyze the price spillovers from oil market to non-ferrous metal markets. In order to start modeling, the specification of the mean equation should be identified. The following mean equation is selected and estimated for each price series:

$$P_t = \mu + \alpha P_{t-1} + \varepsilon_t \qquad (3.1)$$

where, P_t is a $n \, x \, 1$ vector of daily prices between $t-1$ and t, the $n \, x \, 1$ vector of random errors ε_t is the error term for the price on index i at time t. The $n \, x \, 1$ vector μ, represents long-term drift coefficient. A variant of the multivariate GARCH model is used because the possibility of volatility transmission among two markets is analyzed in addition to volatility persistence analysis within each market.

In the literature, several MGARCH parameterizations are presented, such as vector ARCH model (VEC, initially due to Bollerslev, Engle and Wooldridge, 1988), diagonal VEC model (DVEC), the BEKK model (named after Baba, Engle, Kraft and Kroner), Constant Conditional Correlation Model (CCC, Bollerslev, 1990), Dynamic Conditional Correlation Model (DCC models of Tse and Tsui (2002) and Engle (2002)). In this study, the BEKK model is employed because the estimated covariance matrix of equations will be positive semi-definite since it depends on the squares and cross products of error term and volatility for each market. Namely, this model ensures the non-negative estimated variances, and, at the same time does not require estimation of a large number of parameters.

The BEKK parameterization for the multivariate GARCH (1,1) model can be given as:

$$H_t = C'C + A'\varepsilon_t\varepsilon_t'A + B'H_{t-1}B \tag{3.2}$$

where, H_t is the $n\ x\ n$ matrix of conditional variance, C is a symmetric $n\ x\ n$ matrix with constant parameters (c_{ij}), A is a diagonal $n\ x\ n$ matrix of parameters (a_{ij}) which measures the extent of deviations from the mean (i.e., the ARCH term), and B is also a $n\ x\ n$ diagonal matrix of parameters (b_{ij}) which indicates the persistence in conditional volatility between market i and market j (i.e., the GARCH term). In other words, the effects of shocks or volatility can be captured by A.

In our bivariate case, the conditional variance for each equation can be written as:

$$h_{11,t} = c_{11} + a_{11}^2\varepsilon_1^2 + b_{11}^2h_{11,t-1} \tag{3.3}$$

$$h_{22,t} = c_{22} + a_{22}^2\varepsilon_2^2 + b_{22}^2h_{22,t-1} \tag{3.4}$$

and the conditional covariance can be written as:

$$h_{12,t} = c_{12} + a_{11}a_{22}\varepsilon_1^2 + b_{11}b_{22}h_{12,t-1} \tag{3.5}$$

The above equations show the transmission pattern of shocks and volatility between markets and over time. In this study, six models with two variables are estimated to predict current period's variance by forming a weighted average of a long term average (the constant), volatility condition in the previous period (the ARCH term), and the last period's forecasted variance (the GARCH term).

Next the Granger causality-in-variance approach based on squares of the standardized residuals is considered which is developed by Cheung and Ng (1996). The standardized residuals, $u_{it} = {(P_t - \mu_t)}/{h_{it}}$, used in the sample residual cross-correlation function are obtained from MGARCH models, where P_t represent the stationary series and h_{it} is the conditional variance. The squares of the two standardized residuals, $(u_{it})^2$, are obtained for the Granger causality-in-variance and used to derive the sample residual cross-correlation functions between them. The sample residual cross-correlation functions between two squared standardized residuals can be written as;

$$\rho_{u_1u_2}(k) = X_{u_1u_2}(k)\left\{X_{u_1u_1}(0)X_{u_2u_2}(0)\right\}^{-1/2} \tag{3.6}$$

where $X_{u_1u_2}(k)$ is the sample cross covariance function which can be given as

$$X_{u_1u_2}(k) = \begin{cases} T^{-1} \sum_{t=1+k}^{T} u_{1t}u_{2t-k} & ,k \geq 0 \\ T^{-1} \sum_{t=1-k}^{T} u_{2t}u_{1t+k} & ,k < 0 \end{cases} \; and \;\; X_{u_1u_2}(0) = T^{-1} \sum_{t=1}^{T} {u_{it}}^2 \tag{3.7}$$

where T is the sample size. The cross-correlation, $\sqrt{T}\rho_{u_1u_2}(k)$, at different lags has asymptotic normal distribution in large samples and under no causality hypothesis and regularity conditions.

3.4. Empirical Results

First we have to investigate the time series properties of the series. Descriptive statistics for the corresponding return series are presented in Table (3.1). Price return volatility is measured by the standard deviation, which is highest in nickel, followed by lead, zinc, copper, tin, oil and aluminum. In terms of skewness, all of the data series are skewed to the left. According to Malik and Hammoudeh (2007), investors in positively skewed markets would be willing to accept smaller returns than investors in negatively skewed markets when the market is up, provided that the losses are not too serious when the market is down. All series exhibit excessive kurtosis, a fairly common occurrence in high frequency financial time series data. The null hypothesis of normality of The Jarque–Bera statistics are rejected for all return series.

Summary of the results of the unit root tests are given in Table (3.2). ADF, DF–GLS, and PP critical values are sourced from MacKinnon (1991). KPSS critical values are from Kwiatkowski, Phillips, Schmidt, and Shin (1992) and MZα critical values are from Ng and Perron (2001). Elliot, Rothenberg, and Stock (1996) gives the critical values of ERS. Although the results seems to maintain a conflict between the tests, in general all six non-ferrous metal prices and oil price are stationary in levels which means that they are stationary in levels.

Table 3.1 – Descriptive statistics for log returns

	LPALUM	LPCOPP	LPLEAD	LPNICK	LPTIN	LPZINC	LPOIL
Mean	-0.003607	0.028838	0.031660	-0.018965	0.051181	0.006114	0.031026
Median	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.118613
Maximum	4.826176	11.35608	11.18281	15.63461	12.62937	8.773891	8.016617
Minimum	-8.613185	-14.96521	-10.87128	-18.16888	-12.36140	-11.74037	-9.205643
Std. Dev.	1.484822	2.132294	2.443550	2.688935	2.038836	2.270085	1.765930
Skewness	-0.643612	-0.557645	-0.395643	-0.190390	-0.496107	-0.524839	-0.506974
Kurtosis	5.712426	8.104604	5.146865	6.354868	8.951577	5.354081	5.430359
Jarque-Bera	489.7714[a]	1483.346[a]	284.4438[a]	619.4071[a]	1978.046[a]	360.9646[a]	376.7872[a]

Notes to table: [a, b, c] Significant at 1%, 5%, and 10% levels, respectively.

Stationarity of the series is tested so that it is understood that they do not contain unit roots as can be observed from Table (3.2). According to the test results with different specifications the series employed do not contain unit roots.

Table 3.2 – Unit root test results

	LEVEL	ADF	DF–GLS	PP	KPSS	ERS	NP (MZα)
Intercept	LPOIL	-30.24967[a] (0)	-30.04821[a] (0)	-30.40994[a] (9)	0.573191[b] (11)	0.102239 (0)	-631.175[a] (9)
	LPALUM	-37.93146[a] (0)	-8.462779[a] (7)	-37.93148[a] (1)	0.730881[b] (1)	0.117576 (0)	-60.7828[a] (7)
	LPCOPP	-39.77678[a] (0)	-3.008679[a] (11)	-39.65863[a] (9)	1.007609[a] (7)	0.103740 (0)	-5.19327 (11)
	LPLEAD	-35.06245[a] (0)	-2.019194[b] (18)	-35.08604[a] (3)	0.468279[b] (4)	0.071697 (0)	-3.58724 (18)
	LPNICK	-36.83380[a] (0)	-1.935740[c] (10)	-36.83006[a] (8)	0.486622[b] (8)	0.190515 (0)	-4.40567 (10)
	LPTIN	-35.02973[a] (0)	-4.850927[a] (9)	-35.01093[a] (5)	0.228858 (4)	0.111333 (0)	-18.8587[a] (9)
	LPZINC	-37.39598[a] (0)	-8.783922[a] (7)	-37.39501[a] (2)	0.965631 (4)	0.061405 (0)	-70.8203[a] (7)
Trend & Intercept	LPOIL	-30.39388[a] (0)	-12.80274[a] (3)	-30.43469[a] (7)	0.177249[b] (10)	0.261593 (0)	-240.527[a] (3)
	LPALUM	-38.10719[a] (0)	-7.882113[a] (7)	-38.10845[a] (4)	0.211725[b] (6)	0.233878 (0)	-52.1181[a] (7)
	LPCOPP	-40.03118[a] (0)	-5.152675[a] (11)	-40.04963[a] (6)	0.235424[a] (2)	0.186908 (0)	-13.3098 (11)
	LPLEAD	-35.14776[a] (0)	-20.96489[a] (1)	-35.14776[a] (0)	0.219265[a] (1)	0.156521 (0)	-494.132[a] (1)
	LPNICK	-36.90949[a] (0)	-3.692934[a] (10)	-36.90045[a] (7)	0.202120 (7)	0.227075 (0)	-15.1391[c] (10)
	LPTIN	-35.05110[a] (0)	-6.727110[a] (9)	-35.03616[a] (6)	0.183636[b] (5)	0.201831 (0)	-36.8733[a] (9)
	LPZINC	-37.59474[a] (0)	-36.36479[a] (0)	-37.60362[a] (6)	0.214173[b] (8)	0.159675 (0)	-651.455[a] (0)

Notes to table: Numbers in parentheses are the lag lengths. [a, b, c] Significant at 1%, 5%, and 10% levels, respectively. All of the null hypotheses are unit root, except KPSS; however, in KPSS the null is stationarity.

MGARCH models are commonly used to study the relationships between the volatilities of multiple markets (Karolyi, 1995) and help to explain the one market volatility is causing the other markets volatility. MGARCH models can also explain whether the price volatility is transmitted to another price directly (conditional variance) or indirectly (conditional covariances), or a shock within a market increases another markets volatility. Estimated results for each variance equation of the BEKK parameterization for the multivariate GARCH (1,1) model are given in

Table (3.3). Table (3.3) reports the results from the model using the price returns of oil and one metal, subscripted by the numbers 1 and 2, respectively.

Table 3.3 – Results of the bivariate GARCH models

	Independent Variable	ε_1^2	ε_2^2	$h_{11,t-1}$	$h_{22,t-1}$
OIL ALUM	$h_{11,t}$	0.355684 (9.658486)	-	0.962877 (178.3832)	-
	$h_{22,t}$	-	0.076758 (12.46019)	-	0.881465 (92.11086)
OIL COPP	$h_{11,t}$	0.029700 (9.550352)	-	0.982916 (190.5847)	-
	$h_{22,t}$	-	0.070944 (15.37148)	-	0.899451 (126.6809)
OIL LEAD	$h_{11,t}$	0.031407 (9.594076)	-	0.963297 (178.2159)	-
	$h_{22,t}$	-	0.071866 (12.08336)	-	0.912461 (128.6587)
OIL NICK	$h_{11,t}$	0.029364 (9.103366)	-	0.965190 (174.3155)	-
	$h_{22,t}$	-	0.053134 (13.24763)	-	0.925517 (156.4269)
OIL TIN	$h_{11,t}$	0.027503 (9.963412)	-	0.969110 (213.9894)	-
	$h_{22,t}$	-	0.161599 (18.79795)	-	0.743537 (68.34661)
OIL ZINC	$h_{11,t}$	0.028802 (9.502903)	-	0.966298 (185.7786)	-
	$h_{22,t}$	-	0.072956 (13.71279)	-	0.908971 (133.8483)

Notes to table: h_{11} denotes the conditional variance for the oil return series, and h_{22} is the conditional variance for the metal return series. t-values given in parentheses. The multivariate GARCH model uses the BEKK parameterization. Results of estimated mean equation and constants of each variance equation are not reported for the sake of brevity.

The presence of autoregressive conditional heteroscedasticity in oil and metal price couples is confirmed by the significance of the estimated parameters. Our results show significant volatility transmission between the global oil markets and each of the non-ferrous metal markets. Not surprisingly, in all of the models, metal prices are directly positively affected by volatility from the oil market. Namely, all six non-ferrous metal markets receive volatility from the oil market implying that financial market participants of non-ferrous markets can potentially forecast the future changes in each metal market by following developments in global oil market.

Next, we examine the Granger causality-in-variance tests by using the method developed by Cheung and Ng (1996). Cross correlation function of the standardized residuals from the GARCH models of a pair of series under consideration form the basis of Cheung and Ng's (1996) measure of pair-wise causality tests. The correlations measured the linear relationships between the residuals of the bivariate GARCH-models and as these residuals mainly reflect market volatility they are suitable to quantify the systemic risk.

Table 3.4 - Granger causality-in-variance test statistics

	Oil and Aluminum		Oil and Copper		Oil and Lead	
i	lag	lead	lag	lead	lag	lead
0	0.039707	0.039707	6.797082[a]	6.797082[a]	0.667796	0.667796
1	3.519466[a]	-0.5956	14.44245[a]	2.804744[a]	3.60249[a]	0.563115
2	0.216583	0.064975	2.696453[a]	5.613098[a]	-1.04682	-1.22369
3	-0.02527	-0.94213	6.280894[a]	6.302552[a]	0.765258	0.884379
4	-0.6317	-1.12984	9.55129[a]	6.277284[a]	0.238241	0.277948
5	0.342922	0.397068	6.526354[a]	3.786585[a]	0.974621	-1.67851[c]

	Oil and Nickel		Oil and Tin		Oil and Zinc	
i	lag	lead	lag	lead	lag	lead
0	1.689344[c]	1.689344[c]	0.758039	0.758039	0.776087	0.776087
1	3.945412[a]	0.960183	1.714612[c]	-0.18049	3.162105[a]	0.7436
2	-0.66058	1.285056	0.602821	0.231021	0.458433	-0.72555
3	0.487311	0.779697	1.519688	-0.02166	0.848282	0.346532
4	0.046926	0.440385	-1.28145	1.530517	-1.1912	-0.15161
5	1.288666	-0.50175	1.750709[c]	1.072084	-0.4476	-0.40068

Notes to table: Oil Granger causes the first variable in variance if the test statistic is significant for some lags; vice versa if the test statistic is significant for some leads. Superscripts a, b, and c denote significance at 1, 5, and 10% respectively.

Results of the Granger causality in variance tests are presented in Table (3.4). The volatility in world oil markets positively Granger cause the volatility in aluminum returns at lag 1. There is positive bidirectional Granger causality in variance from oil returns to the copper returns and vice versa at all lags. Oil volatility positively Granger cause lead volatility at lag 2, with a positive feedback from lead volatility to oil volatility at lag 5. The volatility in oil market positively Granger cause the volatility in the nickel market at lags 0 and 1, while the volatility in nickel market positively Granger cause the volatility in oil market at lag 0. There is positive unidirectional Granger causality in variance from oil returns to the tin returns at lags 1 and 5. Positive Granger causality exists from oil volatility to zinc volatility at lag 1. The volatility spillover results help to detect the causal relationship between world oil prices and non-ferrous metal prices.

3.5. Summary and Conclusions

In this study the six non-ferrous metals' prices and oil price are used to examine the causal relationships between each non-ferrous metal and oil price by using bivariate nonlinear autoregressive conditional heteroscedasticity models. In the first part of this thesis, we discover that the prices of six non-ferrous metals are governed by the conditional heteroscedasticity effects and according to this study oil price reflects the same characteristics. Since the volatility in metal markets may be related to the volatility in oil market, the multivariate GARCH model is used to form valid residuals for the Granger causality in variance tests. The Granger causality in variance tests is carried out by using the method developed by Cheung and Ng (1996). Our results seem to be in line with the previous studies in that the crude oil market volatility leads all non-ferrous metal markets. The result that there is bidirectional causality in variance between oil and copper is not unusual, since this metal is found to be a good indicator of macroeconomic developments. Because of this feature, it has been referred to as Dr. Copper in the literature. In our study, copper appears to be as important as oil. However, it would be interesting to check whether copper prices and volatilities lead other metals as a future study.

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