ANALYSIS OF EXTREME DEPENDENCE BETWEEN ISTANBUL STOCK EXCHANGE AND BRENT OIL RETURNS USING BIVARIATE EXTREME VALUE THEORY

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Thesis Abstract

Derya Korman, "Analysis of Extreme Dependence Between Istanbul Stock Exchange and Brent Oil Returns Using Bivariate Extreme Value Theory"

In this thesis, the relationship between oil price movements and Turkish stock market is investigated. Given the fact that Turkey is an emerging and oil dependent country, the relationship between stock market behavior and fluctuations in oil prices is analyzed by focusing on extreme observations. Bivariate extreme value methodology is used in order to examine the dependence structure between oil and stock market (ISE100). The residuals of autoregressive integrated moving average (ARIMA) models of stock market index and Brent oil returns are examined by using bivariate extreme value analysis over the period between 1988 and 2012. The overall period studied is subdivided into two phases for analysis. Results of the thesis indicate a higher dependence in the second phase (2000-2012), compared to the first phase (1988-2000). Results also show that in the second phase the extremes on the negative tails coincide more commonly compared to the extremes on the positive tails, which is in line with the current literature findings. A more focused analysis of bivariate extreme value theory (EVT) for the 2008-2012 period is conducted within the thesis and highest dependence of oil prices and stock market is found in this period. However, in general Turkish stock market and oil returns are asymptotically independent in extreme observations, which suggest different diversification strategies for portfolio managers.

Tez Özeti

Derya Korman, "Analysis of Extreme Dependence Between Istanbul Stock Exchange and Brent Oil Returns Using Bivariate Extreme Value Theory"

Bu tezde petrol fiyat hareketleri ve İstanbul Menkul Kıymetler Borsası(İMKB) arasındaki ilişki incelenmiştir. Türkiye için borsa hareketleri ve petrol fiyatındaki dalgalanmalar, ülkenin petrole bağımlı gelişmekte olan bir pazar olması nedeniyle önem kazanmaktadır. Bu tezde borsa ve petrol fiyatları arasındaki ilişki uç gözlemlere odaklanarak gerçekleştirilmiştir. İki değişkenli uç değerler teorisi petrol fiyatları ve IMKB fiyat endeksi arasındaki bağımlılık yapısının analizi için kullanılmıştır. Ardışık bağlanımlı bütünleşik hareketli ortalamalar(ARIMA) metodunun uygulanmasından sonra, kalan borsa endeksi ve petrol fiyat getirilerinin artık değerleri çift değişkenli uç değerler yöntemi ile 1988 ile 2012 dönemi arasında incelenmiştir. Çalışılan dönem analiz için iki alt döneme ayrılmıştır. İkinci dönemde (2000-2012), ilk döneme (1988-2000) kıyasla değişkenler arasında daha fazla bağımlılık ilişkisi tespit edilmiştir. Ayrıca tezde son kriz dönemini de kapsayan, 2008-2012 yıllarına odaklanan çift değişkenli uç değerler analizi yapılmış, petrol fiyatları ve IMKB fiyat endeksi arasında en yüksek bağımlılık ilişkisi bu dönemde tespit edilmiştir. Sonuçlar ikinci dönemde negatif kuyruktaki uç gözlemlerin, pozitif kuyruktaki uç gözlemlere kıyasla daha sık birlikte hareket ettiklerini göstermektedir. Bu bulgu güncel literatür ile örtüşmektedir. Fakat genel olarak sonuçlara bakıldığında, IMKB ve petrol getirilerinin uç gözlemler için asimptotik olarak bağımsız olduğu görülmektedir. Bu tezin sonuçları portföy yöneticilerine ve yatırımcılara, farklı çeşitlendirme stratejileri önermektedir.

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CONTENTS

CHAPTER 1: INTRODUCTION 1

CHAPTER 2: LITERATURE REVIEW 6

CHAPTER 3: METHODOLOGY 16

The Data 16

Models 20

CHAPTER 4: EMPRICAL RESULTS 29

CHAPTER 5: CONCLUSION 39

REFERENCES 42

TABLES

1. Descriptive Statistics...19
2. ARIMA Models 21
3. Bivariate Extreme Model Results for ISE100 and Brent Returns..........................30
4. Bivariate Extreme Model Estimates for ISE100 and Brent Returns......................31
5. Bivariate Extreme Model Results for ISE100 and Brent Returns 2008-2012 33

FIGURES

1. World Primary Energy Consumption, 2011……………………………………...…..1

2. Brent Oil Prices, ISE 100 Stock Index and Major Historical Events… ……...……3

3. Total traded Values of ISE (Million $)……………………………………………….4

4. Brent Oil Prices……………………………………………………………………...17

5. ISE 100 Index……………………………………………………………... ……..17

6. Threshold Choice Plots……………………………………………………………...23

7. Threshold Choice Plots……………………………………………………………...24

8. Mean Residual Life Plots……………………………………………………………25

9. Distribution of Extreme Coinciding Days……………………………...………...32

10. Chi and Chi-Bar Plots 1988 – 2000…………………………………………...…...35

11. Chi and Chi-Bar Plots 2000 – 2012…………………………………...………...36

12. Chi and Chi-Bar Plots 2008 – 2012………………………………………...……...37

SYMBOLS

ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criteria
ARMA	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
BIC	Bayesian Information Criteria
BRIC	Brazil, Russia, India and China
CEE	Central and Eastern European
DCC	Dynamic Conditional Correlation
EVT	Extreme Value Theory
GARCH	General Autoregressive Conditional Heteroskedastic
GARCH-GJR	GARCH Glosten-Jagannathan-Runkle
GCC	Gulf Cooperation Council
GPD	Generalized Pareto Distribution
I.I.D.	Independent and Identically Distributed
ISE100	Istanbul Stock Exchange 100 index
MSCI	Morgan Stanley Capital International
OECD	Organization for Economic Co-operation and Development
POT	Peaks Over Threshold
VAR	Vector Auto Regression
VEC	Vector Error Correction
WTI	West Texas Intermediate

CHAPTER 1

INTRODUCTION

Scarce energy sources and world's growing demand for energy highlight the importance of energy economics. Oil is still the world's leading energy input. Currently, world's primary energy consumption consists of 33% oil, 30% coal and 24% natural gas (British Petroleum, 2012). Considering remaining fossil fuel reserves and current developments in renewable energy, world will still be burning fossil fuels to generate energy -at least- for the next fifty years. World Energy Council (WEC) forecasts world's energy consumption to be doubled by 2050 (WEC, 2007). According to British Petroleum (BP) statistics global energy consumption grew by 5% in 2010 and 2.5% in 2011. All of the net growth in energy consumption is accounted for by emerging countries, OECD countries' consumption being in decline. As it is explained in Basher and Sadorsky (2006), emerging economies tend to be more energy intensive and are exposed to higher oil prices compared to developed countries that are more energy efficient in our day. World's energy consumption shares can be seen in the Figure 1 below.

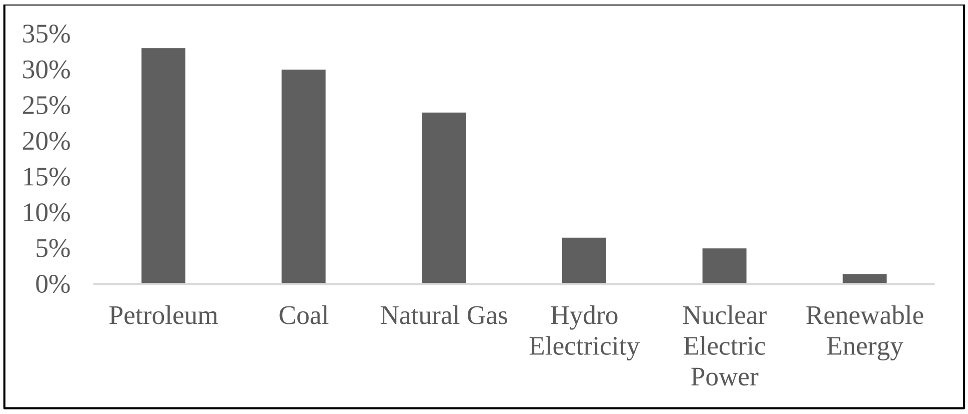


Figure 1. World primary energy consumption, 2011

Source: BP Statistical Review of World Energy June 2012.

Oil prices fluctuated unprecedentedly during the past decade. There are many variables and incidents that affect the world crude oil prices, but some of the events had a major effect on the crude oil market. On August 2, 1990, Iraq invaded the Kuwait, causing a sharp rise in crude oil to $41 per barrel and crude oil products. U.S. attacked to Iraq on January 16, 1991, which led crude oil prices to drop sharply. Collapse of Soviet Union at December 1991, led to a decline in the oil supplies. Asian crisis of 1998 decreased oil demand, therefore prices plunged as low as $9.55 per barrel. The bottom line of oil market is observed in 1998 and thereafter oil prices started to increase in a fast pace. Terrorist attack to the U.S. World Trade Center at September 11, 2001, affected the oil prices negatively; crude oil and product futures fell to their lowest levels in 2 years. Iraq invasion at March, 2003, led by U.S., reduced Iraq's oil supply to the market. Uncertainty of the market combined with growing demands of big emerging markets such as China, India and Russia, which leads to increase in oil prices. At 2008, oil prices rose up to record high $145 per barrel. Sell-offs began in world markets in the second half of 2008 with global recession fears. After the Federal Reserve of U.S. indications, crude oil prices fell to $128 per barrel range. After Lehman Brothers' bankruptcy, September 2008, oil prices decreased below $90 and hit record low in February 2009, to nearly $35 per barrel. Later 2009, crude oil prices started to increase steadily with the help of rising demand from Asia. Following political turmoil in the Arab world starting at the end of 2010, crude oil prices reached over $120 a barrel at April 2011. In 2012, oil prices stay over $100.

Increasing oil prices, particularly starting from 2000s, have a considerable effect on macroeconomic variables such as growth rate, foreign trade balance and inflation, especially for emerging countries. Brent oil prices at the top and ISE100 index at the bottom covering the period 1988 to 2011 with major historical events is presented in the Figure 2.

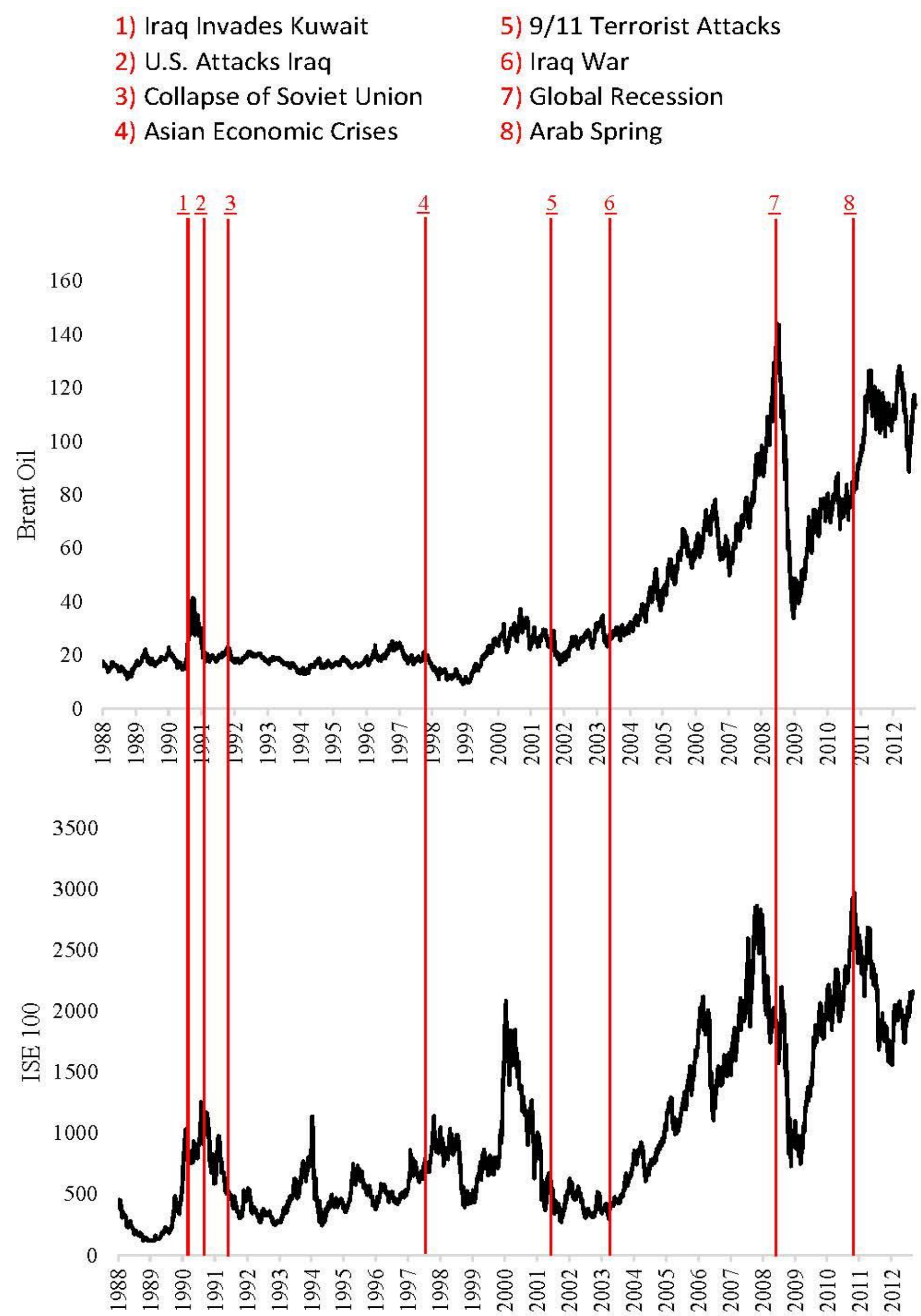


Figure 2. Brent oil prices, ISE 100 stock index and major historical events

Source: For brent oil data; U.S. Energy Information Administration. For ISE 100 index; www.ise.org

Istanbul Stock Exchange was established in December 1985. ISE started its activities with forty firms and an average daily transaction volume of fifty thousand USD. According to the 2011 figures, there are 363 traded companies and daily transaction volume is 1.7 billion USD. As of 2011, the total traded value of stock market is 424 billion USD. Figure 3 presents total traded values of ISE between 2002 and 2011.

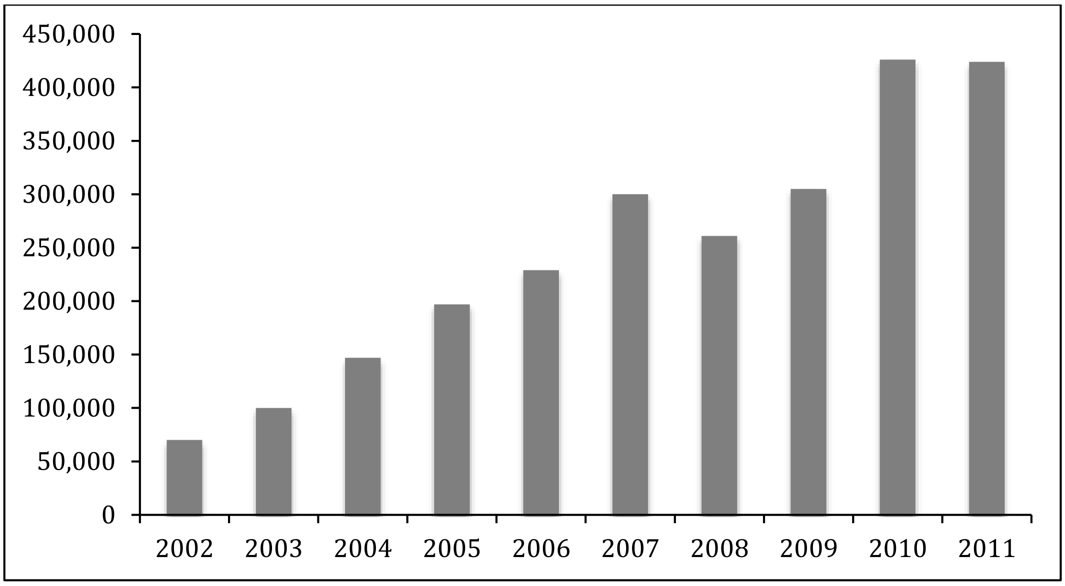


Figure 3. Total traded values of ISE (million $)
Source: www.ise.org

This thesis investigates dependence between oil prices and Turkish stock market. After 1980s, Turkey's energy consumption increased excessively due to industrialization process and growth in population. Crude oil constitutes more than forty percent of Turkey's energy requirements. About nine percent of Turkey's total imports consist of crude oil. Yanar and Kerimoğlu (2011) argue that there is a positive relationship between energy consumption and current account deficit in Turkey. They also indicate that increasing energy imports have positive impact on growth and changes in the current account deficit also affect growth. Considering importance of oil in Turkish economy, one can say that oil prices have a decisive effect on macroeconomic indicators. Despite various researches done on macroeconomics of energy matter, there is relatively limited number of researches, which concentrate on financial markets' reaction to the energy prices.

During the last decade, considerable amount of extreme price movements for oil and stock markets are observed. In the volatility of our times, extreme price movements become a familiar phenomenon. Oil and stock market relationship examined by the current literature mainly focused on analyzing central observations. Motivation of this thesis is to analyze reaction of Turkey's stock market to extreme oil price movements, since Turkey is an oil dependent emerging country. This approach may help to understand the behavior of emerging financial markets in volatile conditions and times of crisis.

CHAPTER 2

LITERATURE REVIEW

Numerous researchers through the last two decades have studied oil price effect on macroeconomic variables. Hamilton's (1983) study can be considered as a starting point in the literature of this subject. He analyzed various macroeconomic indicators of U.S. and oil prices and concluded that postwar recessions preceded by positive oil price shocks however these increases in the oil prices are not a sufficient factor for postwar recessions. Hamilton's study followed by other researches, which can be shown as one of the first contributions to the literature, such as; Gisser and Goodwin (1986) test the effect of crude oil prices to macro economy in U.S. They find that crude oil prices have a significant effect on broad range of macroeconomic indicators. They conclude that crude oil prices have both real effects and inflationary effects. Mork (1989) extended Hamilton's (1983) study by including oil market collapses in 1980s and correcting the oil price variable. His results confirm that negative correlation with the oil price increases persist in the longer sample period and are strengthened by the oil price correction. Considering the number of researches that have analyzed the oil price effect, there is relatively a small number of works that focused on the stock markets.

Going through the literature, many of the findings represent a negative relationship between oil prices and stock markets. Jones and Kaul's (1996) study was the first to reveal negative impact of oil prices on stock exchanges. They study the real impact of oil prices on stock markets of United States, Canada, Japan and the United Kingdom by using regression models during the postwar period. They show that oil prices have a detrimental effect on output and stock returns in these countries. They explain the effects of oil price shocks for U.S. and Canadian stock markets using changes in financial variables and future cash flows, however they could not explain the oil price effects for Japan and United Kingdom's stock markets. Sadorsky (1999) finds a negative relationship between stock markets and oil prices, where positive shocks to oil prices depress the real stock returns. He employs a vector auto regression model (VAR) on monthly data of real stock returns and real oil prices covers 1947-1996 for U.S. market. He also reports a change in oil price dynamics that after 1986 oil price explains a larger fraction of forecast error variance in stock returns. According to his research, oil price and oil price volatility have an important role in affecting economic activity but on the contrary economic activity have a little effect on oil prices. In the study of Papapetrou (2001), dynamic relationship among oil prices, real stock prices, real economic activity, employment and interest rates for Greece was analyzed. He uses a multivariate VAR model on monthly data from 1989 to 1999 and find that oil price shocks has a negative effect on stock returns that lasts for approximately 4 months. An increased number of researches can be observed after 2000's together with more diversified findings on oil and stock market relationship.

In the recent literature, some of the negative oil and stock market relationship findings continue as follows: Hammoudeh and Li (2005) use vector error-correction (VEC) model on daily data of 3-month oil future price, the Morgan Stanley Capital International Index and four oil sensitive international stock market indices in their study. As for oil future price, they use future prices of West Texas Intermediate (WTI). They reveal a negative bidirectional dynamic relationship between oil future price and Morgan Stanley Capital International (MSCI) global equity index. At the individual country and industry levels MSCI returns and oil future price growth lead oil sensitive stock returns with MSCI having the stronger influence. They also point out that systematic risk is greater than oil price growth impact on oil sensitive stock returns used in their study. They suggest investors should give more emphasis on world market return rather than oil price increases, for pricing oil sensitive stocks. Park and Ratti (2008) examine effect of oil price shocks by applying VAR analysis on US and 13 European countries stock indices over the period 1986 - 2005. They conclude that oil price shocks have a statistically significant impact on real stock returns in the same month or within one month and they also conclude that oil price shocks have a negative impact on real stock returns except for Norway and US. Norway as an oil exporter, Norwegian stock returns show a positive significant response to an oil price increase. Park and Ratti also mention that effect of oil price shocks to variability in real stock returns is greater than interest rate in the U.S. and most other countries. Miller and Ratti (2009) utilize a cointegrated VEC model to investigate the relationship between crude oil prices and stock markets of six OECD countries over the period between 1971 and 2008. They reveal a significant negative long-run relationship between oil prices and stock indices, except for the period of 1980-1988, where they find no significant relationship and the reversal in some of the countries after 1999. They also indicate a change in the correlation between oil price and stock markets in the last decade compared to earlier years. Bhar and Nikolova (2010) conduct bivariate exponential general autoregressive conditional heteroskedastic (GARCH) model on weekly data of Russian AK&M Composite index and WTI crude oil prices over the period 1995-2007. They identify that changes in the global oil prices have a significant effect on volatility and prices of Russian equity market. Oil price spillovers are largely determining the Russian equity prices. They also find a negative time varying conditional correlation between

Russian equity market and oil price where this correlation is more significant after second half of 1998. They advise a strategy which promotes diversification of operations to ensure longer term economic growth and stability in the long term for Russian stock exchange market which has a high concentration of oil producing companies. Filis (2010) examines relationship between oil prices, stock market, consumer price index and industrial production in Greece by using a VAR approach. He uses monthly data for the series covers the period 1996 and 2008. He observes negative and significant influence of oil price on Greek stock market as well as that a high percentage error variance of Greek stock market derives from oil prices. As a result of his study, author suggests that Greece should rely more on its fiscal policy rather than monetary policy for oil price absorption since oil price shocks influence country's stock market and inflation. Lee and Chiou (2011) employ a regime-switching model to examine the impact of oil shocks on stock returns. They used daily data of U.S. S&P 500 stock index and WTI crude oil prices over the period 1992 to 2008. Their results show a negative and statistically significant impact of oil prices on US stock returns but only in a regime of high oil price fluctuations. Their results do not hold for a regime state of low oil price fluctuations. They suggest a well-diversified portfolio to increase the accuracy of hedging against oil price risks as a result of their findings.

Recent findings also show positive relationship between oil and stock markets. Basher and Sadorsky (2006) apply international multi-factor model on daily data of 21 emerging stock markets, MSCI and WTI crude oil between the periods 1992-2005. Their results show that oil price risk plays an important role in pricing emerging stock markets and oil price risk is statistically significant and positive at 10% level in most models. Their results also reveal an interesting aspect for oil and stock market relationship. Nature of the relationship depends on data frequency being used in the analysis. They argue that for daily and monthly data, oil price increases affects emerging stock market returns positively, whereas for weekly and monthly data, oil price decreases affects emerging stock markets returns positively. Constantinos et al. (2010) estimate a VAR model with granger causality tests on daily data of Greek stock market returns and international crude oil price between 2004 and 2006. They indicate a significant positive association between Greek stock market and oil prices. They also find evidence of bi-directional causality between stock market returns and stock market volatility, as well as significant positive casual effects running from oil price and oil price volatility towards the stock market returns. Choi and Hammoudeh (2010) conduct Markow-switching GARCH models on weekly data for WTI oil, Brent oil, gold, silver, copper and U.S. S&P500 index covers the period 1990-2006. They use two different GARCH models; first model is univariate Markow-swithcing heteroskedasticity model with two regimes and the second model is the dynamic conditional correlation (DCC) multivariate GARCH model. Their findings show that WTI oil has the highest volatility followed by Brent oil, both in high and low volatility regimes. Brent and WTI are not perfect substitutes in the means of volatility. They also argue that in high volatility regimes, there is a positive probability correlation between S&P500 index and crude oil prices. Narayan and Narayan (2010) study the impact of WTI crude oil prices on Vietnam's stock prices by conducting a long-run model. They use daily data during the period 2000 to 2008 and they also include the exchange rate as an additional determinant of stock prices. They conclude that oil prices, stock prices and exchange rates have a long-run relationship, where oil prices and exchange rates have a significant positive effect on stock prices. As a reason for this positive relationship, they identify two factors;

increasing foreign portfolio investment inflows and change of local market participant’s preferences from holding domestic bank deposits and foreign currencies to stocks. Zhu et al. (2011) investigate the relationship between stock markets for 14 Organization for Economic Co-operation and Development (OECD) and non-OECD countries and WTI crude oil from 1995 to 2009. They use panel-based tests (co integration and unit root tests), VEC models and Granger casualty tests with monthly data for their analysis. Their tests show evidence for the existence of a bidirectional long run Granger-causal relation between crude oil and stock markets. However, results of their analysis also indicate that increased oil prices have a positive impact on stock prices and increased stocks influence crude oil positively. Influence of stock prices on oil prices is not inline with the theoretical expectation. They argue that this finding is reflecting the fact that oil stocks contained in the stock prices. Ono (2011) applies a multivariate VAR model on Brazil, Russia, India and China’s (BRIC) stock returns and oil prices over 1999-2009 with monthly data. He finds a significant positive relationship between them, except for Brazil. He also reveals significant asymmetric effects for India. His analysis of variance decomposition for China and Russia indicates that contribution of oil price shocks to volatility is relatively large and significant. Basher et al. (2012) utilize structural VAR model on monthly data of exchange rates, oil prices and emerging stock prices over the period 1988-2008. They conclude that unanticipated oil demand expansions generate small positive impact on stock returns, which is statistically significant for 3 months. They also find that exchange rates respond to movements in oil prices. Li et al. (2012) use panel cointegration test and Granger causality analysis to examine the relationship between oil price and Chinese stocks at sectoral level. They analyzed monthly data during the period 2001 to 2010. They reveal that in the long run, real oil price has a positive impact on sectoral stocks. They also find a unidirectional long run and short run Granger causality relationship running from oil prices and stocks to interest rates for 2001-2005 period.

A part of the literature suggests that there is a conditional relationship between oil and stock market or no relationship at all. Huang et al. (1996) investigate the effects of oil future prices to US SP500 stock index on different levels by using a VAR approach on daily data series from 1979 to 1990. They provide that there is no relationship between oil futures and broad based stock index. However, on the firm level they discover a significant relationship, oil future returns leads oil stock returns by one day. Faff and Brailsford (1999) analyze the sensitivity of Australian industry equity to oil price factor. They conduct augmented market model on monthly data of oil price and 24 Australian industry portfolios over the period 1983-1996. Their findings indicate a positive sensitivity for diversified industrial resources and oil and gas portfolios together with a negative sensitivity for transportation and paper and packaging portfolios. Maghyereh (2004) utilize VAR analysis to investigate dynamic linkages between 22 emerging country's stock market returns and Brent oil prices. He uses monthly data for the period 1998 to 2004. His results provide very weak evidence of a relationship between stock returns and oil price in the emerging economies. Results also reveal that innovations in the oil market are slowly transmitted in the emerging stock indices. Hammoudeh and Choi (2006) use VEC model on 5 GCC countries stock markets, oil prices, U.S. T-bill rate and SP500 market index by using weekly data over 1994-2004. They assert that oil price do not seem to have a significant relationship with GCC country's stock markets, whereas T-bill has a short term impact on some GCC countries. Malik and Hammoudeh (2007) estimate a multivariate GARCH model with BEKK parameterization on daily data to identify volatility and shock transmission mechanism among U.S. equity WTI crude oil price and equity markets of Saudi Arabia, Kuwait and Bahrain. They conclude that Gulf equity markets receive volatility from oil market. They also discover that only in Saudi Arabia, there is volatility spillover from Saudi equity market to world oil market, as well as news or shocks in U.S. equity market indirectly affect the volatility in Gulf equity markets. As a result of their study, authors advise that financial derivatives such as index options that can provide a hedge against index return volatilities may be introduced for using these derivatives to reduce Gulf Cooperation Council (GCC) market invertor's risk at times of heightened volatility. Eryigit (2009) applies Faff and Brailsford's (1999) augmented market model on 16 sector indices of Istanbul Stock Exchange with daily data from 2000 to 2008. He demonstrates that oil price affects sector indices differently. Oil price changes have significant and positive effect on these sectors at %5 level; electricity, wholesale and retail trade, insurance, holding, investment, wood, paper and printing, basic metals, metal products and machinery, mineral products. He also indicates that oil price changes have no significant effect on industries such as; banks, leasing and factoring, real estate investment trust. Al-Fayoumi (2009) examine the relationship between Brent oil prices and 3 oil importing countries, which are Turkey, Tunisia and Jordan, by using VEC model and Granger causality test on monthly data from 1997 to 2008. He reports that oil price do not adversely affect Turkish, Tunisian and Jordan stock prices and effect of local macroeconomic variables are more important than oil prices. Mohanty et al. (2010) analyze the relationship between WTI oil prices and oil and gas firms in Central and Eastern European (CEE) countries by using monthly returns. They apply linear factor pricing model on monthly returns between 1998-2010 period. They find that there is no significant relationship between equity values of oil and gas firms and oil prices. They also couldn't find any relationship on the industrial level, except for Austria, which is the only developed country in the analysis. Hearn and Man (2010) apply VAR model on monthly data of stock indices of China and Hong Kong and Brent crude oil prices in the period 2000 to 2010 to examine the degree of price integration. They observe short-term influences on Hong Kong stock market index by the changes in oil prices. However, they conclude that there is general lack of long-term price integration between markets and oil price. Laopodis (2011) examine the dynamic linkages between oil prices and stock markets by using rolling sample cointegration technique and VAR model. They use monthly data for France, Germany, Italy, U.K., U.S. and oil prices in the period 1990 to 2009. They split their sample into pre Euro (1990-1998) and post Euro (1998-2009) for the analysis. They reveal that oil prices do not explain much of the fluctuations in the stock market returns except for U.S. Filis et al. (2011) investigate the time-varying correlation between oil prices and six country's stock market prices, in which three of them are oil exporter countries and three of them are oil importer countries, with monthly data during the period 1987 to 2009. They use DCC-GARCH Glosten-Jagannathan-Runkle (GJR) approach in their analysis. Their results show that oil price shocks during global business cycle fluctuations, both negative and positive, have a significant effect on oil-stock relationship, regardless of the country's oil dependence status. Oil shocks originated from products cuts, hurricanes etc., do not seem to have a significant impact on oil-stock market relationship. Their results also demonstrate that time-varying correlation of oil and stock prices do not differ for oil importer and oil exporter countries. They assert that precautionary demand side oil shocks tend to cause negative correlation, whereas aggregate demand side shocks cause positive correlation. Supply side shocks do not have any impact oil-stock relationship.

Contribution of this thesis to the existing literature will be using bivariate extreme value theory for analyzing the dependence structure of stock market and oil prices. As it is mentioned in some of the studies such as: Choi and Hammoudeh (2010) and Lee and Chiou (2011), different volatility regimes have different oil price effect on stock markets. High volatility environment has many extreme events in terms of oil price and stock market movements, which also illustrates our global market structure in the last decade. Instead of the normal price behavior of crude oil, this thesis will focus on extremal events by using a bivariate extreme value methodology on an emerging market, Turkey.

CHAPTER 3

METHODOLOGY

The Data

In this thesis, daily data is used for crude oil prices and stock market index. The daily data covers the period from January 1988 to August 2012. Brent oil prices are used as the crude oil prices since Brent oil index is the main indicator for Turkish oil trade. Oil price data come from U.S. Energy Information Administration (EIA). Istanbul Stock Exchange 100 (ISE 100) closing prices are used as the stock market data. Stock market data is taken from Istanbul Stock Exchange web site (www.ise.org). Both oil and stock prices are expressed in US dollars. Data is analyzed using the R Project software, which is an open source language and environment for statistical computing. Our data set consists of log returns of spot prices and there are a total of 5978 observations excluding missing days for oil price and stock index. Considering the chronological events of late 1990s and 2000s such as; (1998) Asian economic crisis, (2001) 9/11 terrorist attacks, (2003) Iraq war and 2008 global recession, we divide our dataset into two phases. The first phase covers the years 1988-2000 and the second phase covers the years through 2000-2012. The data covers a period of 24 years during which we observe a shift in scale of prices and volatility both in oil and stock markets. Figure 4 and 5 show Brent oil and ISE 100 index prices against the time, respectively. The vertical lines in these figures show our cut-off point between two phases.

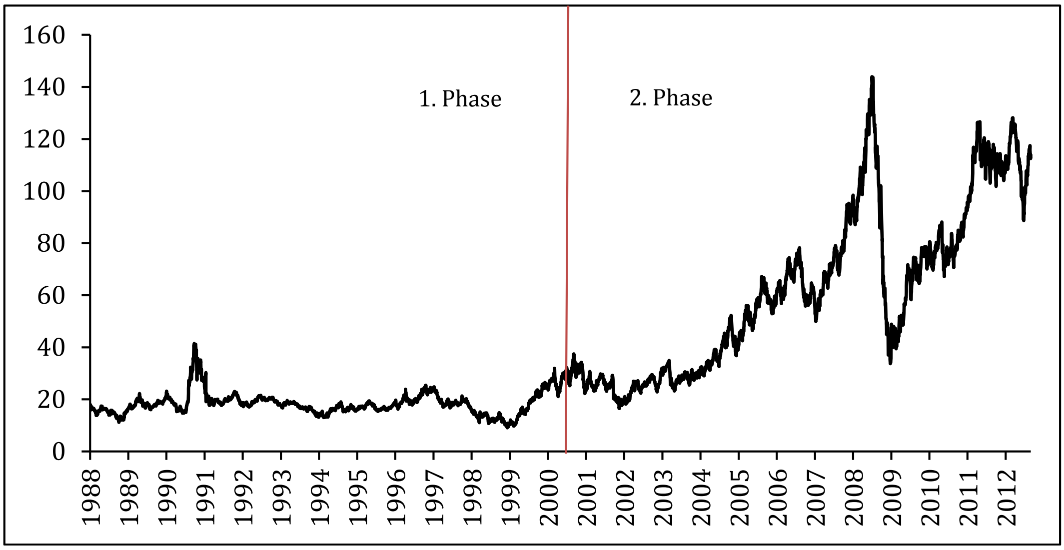


Figure 4. Brent oil prices

Source: U.S. Energy Information Administration

Figure 5. ISE 100 index

Source: www.ise.org

Descriptive statistic results for Brent oil and ISE 100 returns are provided in Table 1. Standard deviation figures indicate that ISE 100 index returns are more volatile compared to oil returns in both phases. Mean and median values are close to the central value for all data sets. Maximum and minimum values show that highest daily loss occurred in the first phase, whereas highest daily gain occurred in the second phase for both Brent oil and ISE 100 index. Results of the Jarque-Bera test shows that oil returns and ISE 100 index returns are not normally distributed at both phases. Kurtosis values also indicate the same result. Positive excess kurtosis values show that data for both phases have heavy tails, especially Brent oil at the first phase, which implies that tails of the distribution have more mass on them compared to a normal distribution. It can also be said that distributions with high excess kurtosis values contains more extreme values. Skewness values of data sets are slightly negative, which indicates that left tail of the distribution is slightly longer than the right tail.

Augmented Dickey-Fuller (ADF) test shows us that our data set at both phases are stationary. Data set used in this study is not independent and identically distributed (*i.i.d.*) except for oil returns at the second phase according to Ljung-Box test statistics. To test data with bivariate extreme value model, data set needs to be converted into i.i.d. series. We utilized an ARIMA model for the data conversion process. Details of the ARIMA model will be explained in the model section.

Table 1. Descriptive Statistics

Statistics	Phase 1		Phase 2	
	Brent	ISE 100	Brent	ISE 100
Mean	0.0001	0.0004	0.0005	0.0003
Median	0.0000	0.0000	0.0014	0.0008
Maximum	0.1733	0.2499	0.1813	0.2500
Minimum	-0.3612	-0.2538	-0.1989	-0.2367
Std. Dev	0.0238	0.0335	0.0242	0.0313
Skewness	-1.117	-0.2223	-0.3145	-0.1969
Kurtosis	23.497	4.961	5.540	7.257
Jarque-Bera	69,484.6***	3,095.9***	3,880.8***	6,592.4***
Augmented Dickey-Fuller	-12.798***	-12.718***	-12.086***	-12.469***
Ljung-Box	8.868***	61.767***	0.2595	18.749***
[p-value]	*[0.0029]*	*[0]*	*[0.6105]*	*[0.0000]*
Observations	2989	2989	2989	2989

This table shows descriptive statistics for Brent oil log-returns and ISE 100 index log-returns for the two phases. Phase 1 and phase 2 cover the periods from 1988 to 2000 and from 2000 to 2012, respectively. In each phase 2989 daily observations are used, as the extreme value methodology requires high frequency data. ***, **, * Denote significance at the 1%, 5%, and 10% levels, respectively.

Before the extreme value analysis, data set is examined with simple Pearson correlation. Correlation between oil prices and ISE 100 prices is 0.86, which indicates these two series is moving very similarly. Dividing our price data into two phases, correlation value of 0.37 is observed for the first phase and 0.83 is observed for the second phase. Second phase of the dataset has a higher correlation value compared to first phase, which justifies dividing the dataset into two phases for further analysis in this thesis. For the return data, also a higher correlation value is observed for the second phase. Correlation coefficients are -0.03 and 0.14 for the first phase and second phase respectively.

Models

Arima Model

Box and Jenkins (1970) methodology defines the ARIMA models for forecasting process. These models are also called Box-Jenkins models in the literature. As it is briefly explained in the Cryer and Chan (2008), a time series $\{Y_t\}$ is following an ARIMA model, if the d^{th} difference $W_t = \nabla^d Y_t$ is a stationary Auto Regressive Moving Average (ARMA) model. If $\{W_t\}$ follows an ARMA (p,q) model, $\{Y_t\}$ can be considered as an ARIMA (p,d,q) process. *With* $W_t = Y_t - Y_{t-1}$, ARIMA (p,1,q) can be defined as;

$$W_t = \emptyset_1 W_{t-1} + \emptyset_2 W_{t-2} + \ldots + \emptyset_p W_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q}$$

Data set is examined according to Akaike information criteria (*AIC*) and Bayesian information criteria (*BIC*) to get the best-fitted ARIMA model possible. Akaike's (1973) study proposed criteria to determine the order of an AR process, which is identified as;

$$\text{AIC} = -2log(maximum\ likelihood)\ +2k$$

where $k=p+q$ and $k=p+q+1$ if the model contains a constant term or intercept. BIC method for determining the order of an AR process is identified in Schwarz's (1978) work. Bayesian information criteria can be defined as;

$$\text{BIC} = -\frac{2}{T} ln(maximum\ likelihood) + klog(n)$$

Tools for selecting AIC and BIC values are provided in Hyndman's (2011) package 'forecast'.

Statistical results for Ljung-Box tests and lag order of ARIMA models are represented in Table 2. For the data series ARIMA models are applied to remedy the autocorrelation and transforming the data into i.i.d. series, Ljung-Box figures show that data sets are i.i.d. after fitting the model. However, for Brent oil returns in the second phase, no modeling was necessary or required.

Table 2. ARIMA Models

Statistics	Phase 1		Phase 2	
	Brent	ISE 100	Brent	ISE 100
ARIMA Model	ARIMA(1,0,4)	ARIMA(4,0,4)	ARIMA(0,0,0)	ARIMA(0,0,1)
Ljung-Box *[p-value]*	0.0009 [0.9758]	0.017 [0.8964]	0.2595 *[0.6105]*	0.0087 [0.9257]

This table shows fitted ARIMA models and Ljung-Box statistics for oil log-returns and ISE 100 index log-returns for the two phases. Phase 1 and phase 2 cover the periods from 1988 to 2000 and from 2000 to 2012, respectively. In each phase 2989 daily observations are used, as the extreme value methodology requires high frequency data. Data set is examined according to *AIC* and *BIC* criteria to get the best-fitted model possible.

ARIMA models for the data series can be defined as below, since AIC and BIC values indicate 0 non-seasonal differences for the models, ARMA models is used for our data conversion process. Numbers in the parenthesis are the actual values for the ARMA model.

Brent oil Phase1 : $Y_t = \emptyset Y_{t-1} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \theta_3 e_{t-3} - \theta_4 e_{t-4}$

$Y_t = (-0.8011)Y_{t-1} + e_t - (0.8546)e_{t-1} - (0.0008)e_{t-2} - (-0.0863)e_{t-3} - \theta_4(-0.044)e_{t-4}$

ISE100 Phase 1 : $Y_t = \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \emptyset_3 Y_{t-3} + \emptyset_4 Y_{t-4} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \theta_3 e_{t-3} - \theta_4 e_{t-4}$

$Y_t = (-0.4994)Y_{t-1} + (0.4288)Y_{t-2} + (0.3774)Y_{t-3} + (0.4316)Y_{t-4} + e_t - (0.6590)e_{t-1} - (-0.3880)e_{t-2} - (-0.4946)e_{t-3} - (-0.4178)e_{t-4}$

ISE100 Phase 2 : $Y_t = e_t - \theta_1 e_{t-1}$

$Y_t = e_t - (0.0831)e_{t-1}$

Extreme Value Theory

Bivariate extreme value methodology is used in this thesis to investigate the dependence between stock market and oil returns. Extreme observations on the tails of a distribution have an important influence over the model. Extreme value theory ignores the central observations and focuses on the tails of the distribution. Theory uses proper mathematical models for identifying and learning the probabilities of extreme observations.

Dodd's (1923) study can be considered as modern day study of extreme events, which is followed by Frechet (1927) and Fisher-Tippett (1928). Various important researches can be found in the existing literature on the subject. Focusing on more recent studies, Resnick (1987), Galambos(1987), Reiss (1993) are the first to study multivariate extremes in their works.

Extreme value method is used to block extrema or exceedances to a predetermined threshold. Determining the threshold level is crucial for extreme value analysis. A low threshold level would cause selecting samples from central part of the distribution, while a high threshold level would eventuate with insufficient data and inaccurate estimates. Threshold level for our data series is determined as tenth percentile for the lowest returns and ninetieth percentile for the highest returns. Threshold levels are determined visually by using threshold choice plots and mean residual life plots provided in Figure 6, Figure 7 and Figure 8.

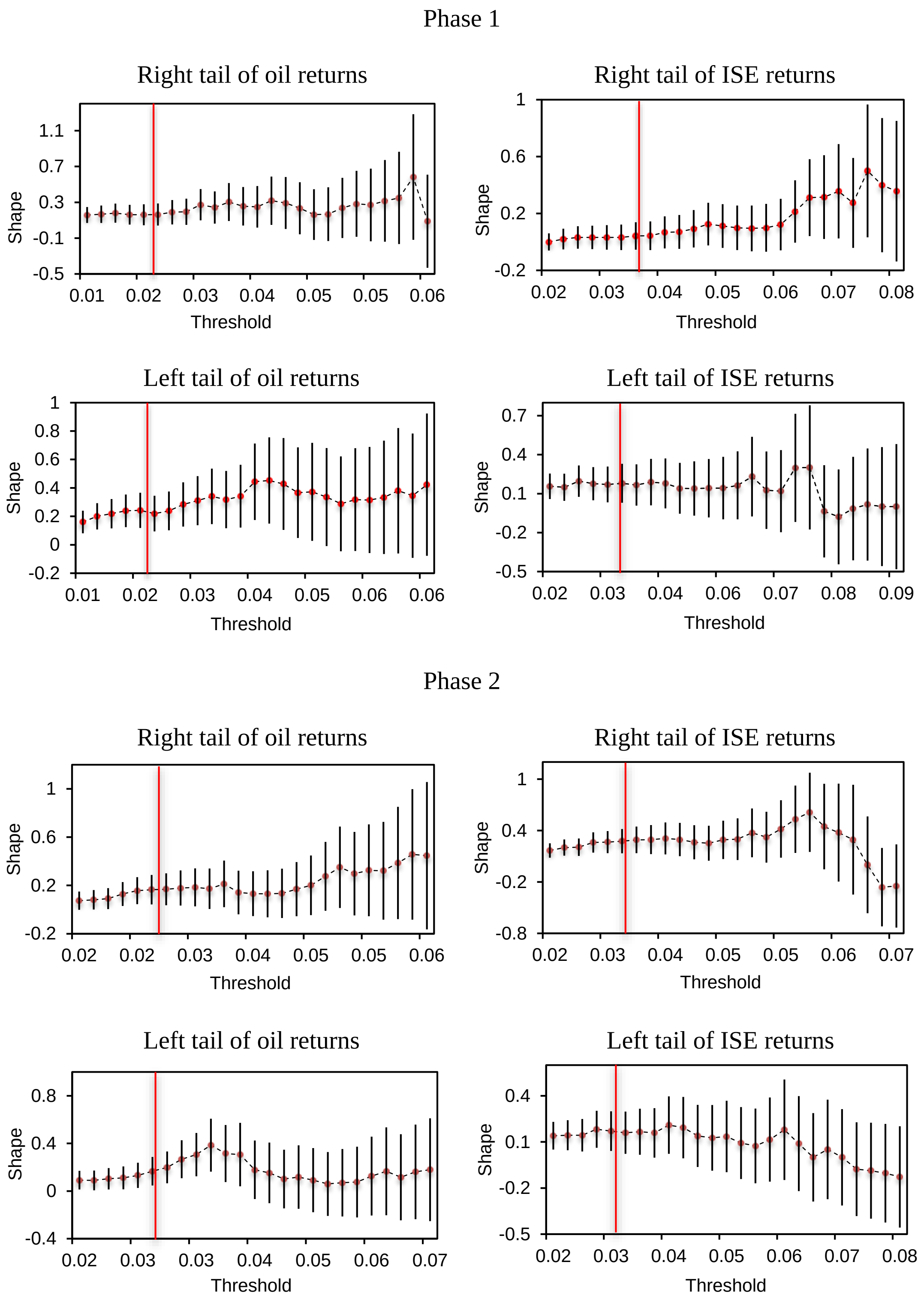


Figure 6. Threshold choice plots

The figure presents threshold choice plots for the left and right tails of oil returns and ISE 100 returns. The figure shows how the estimated shape parameter changes with different choices of thresholds. For each threshold level, the estimated parameter is plotted within a 95% confidence interval. The thresholds selected are marked with the longitudinal vertical lines that correspond to ninetieth quantile for the right tails and tenth quantile for the left tails. The estimated scale and shape parameters are expected to be constant after the threshold selected.

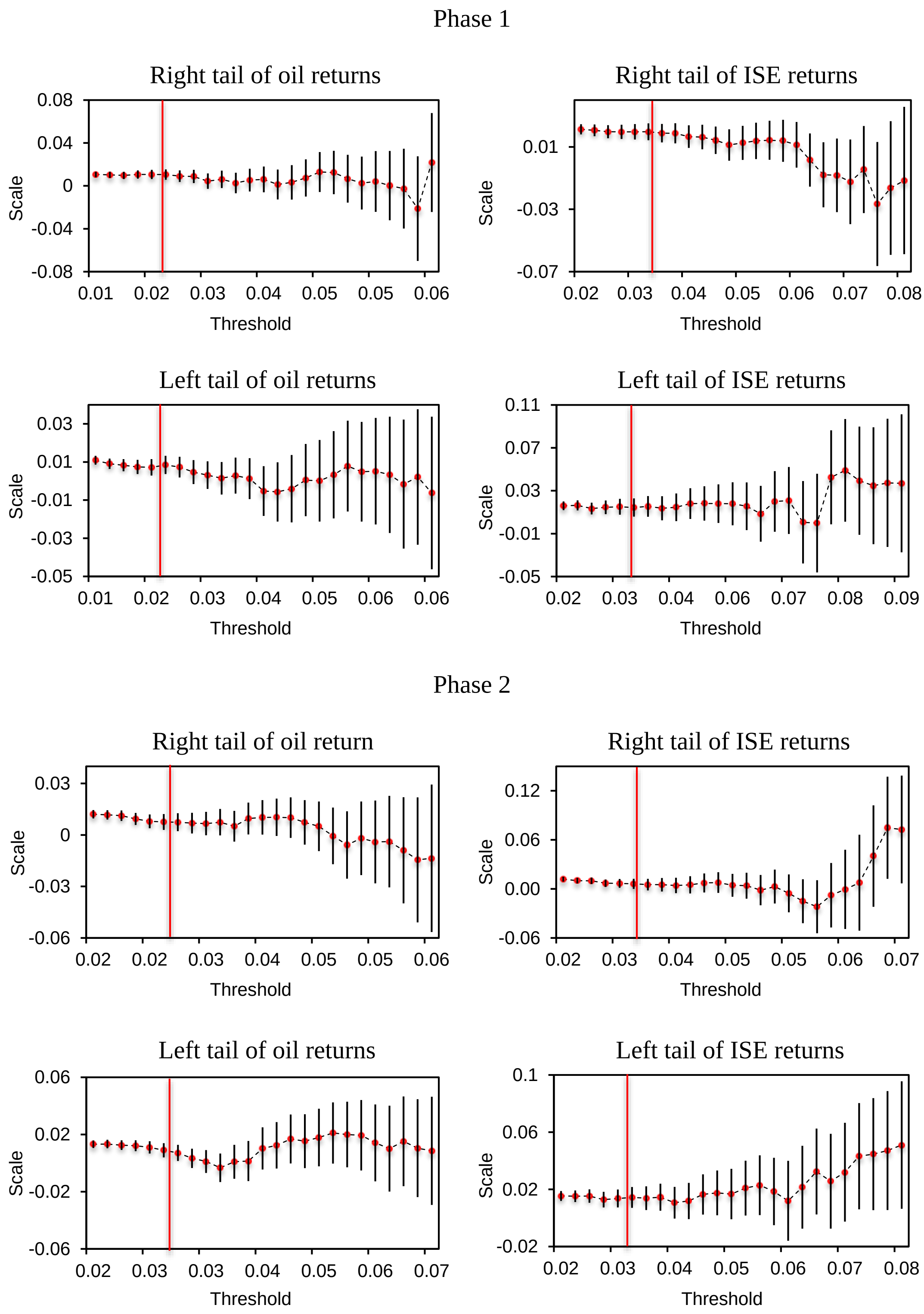


Figure 7. Threshold choice plots

The figure presents threshold choice plots for the left and right tails of oil returns and ISE 100 returns. The figure shows how the estimated scale parameter changes with different choices of thresholds. For each threshold level, the estimated parameter is plotted within a 95% confidence interval. The thresholds selected are marked with the longitudinal vertical lines that correspond to ninetieth quantile for the right tails and tenth quantile for the left tails. The estimated scale and shape parameters are expected to be constant after the threshold selected.

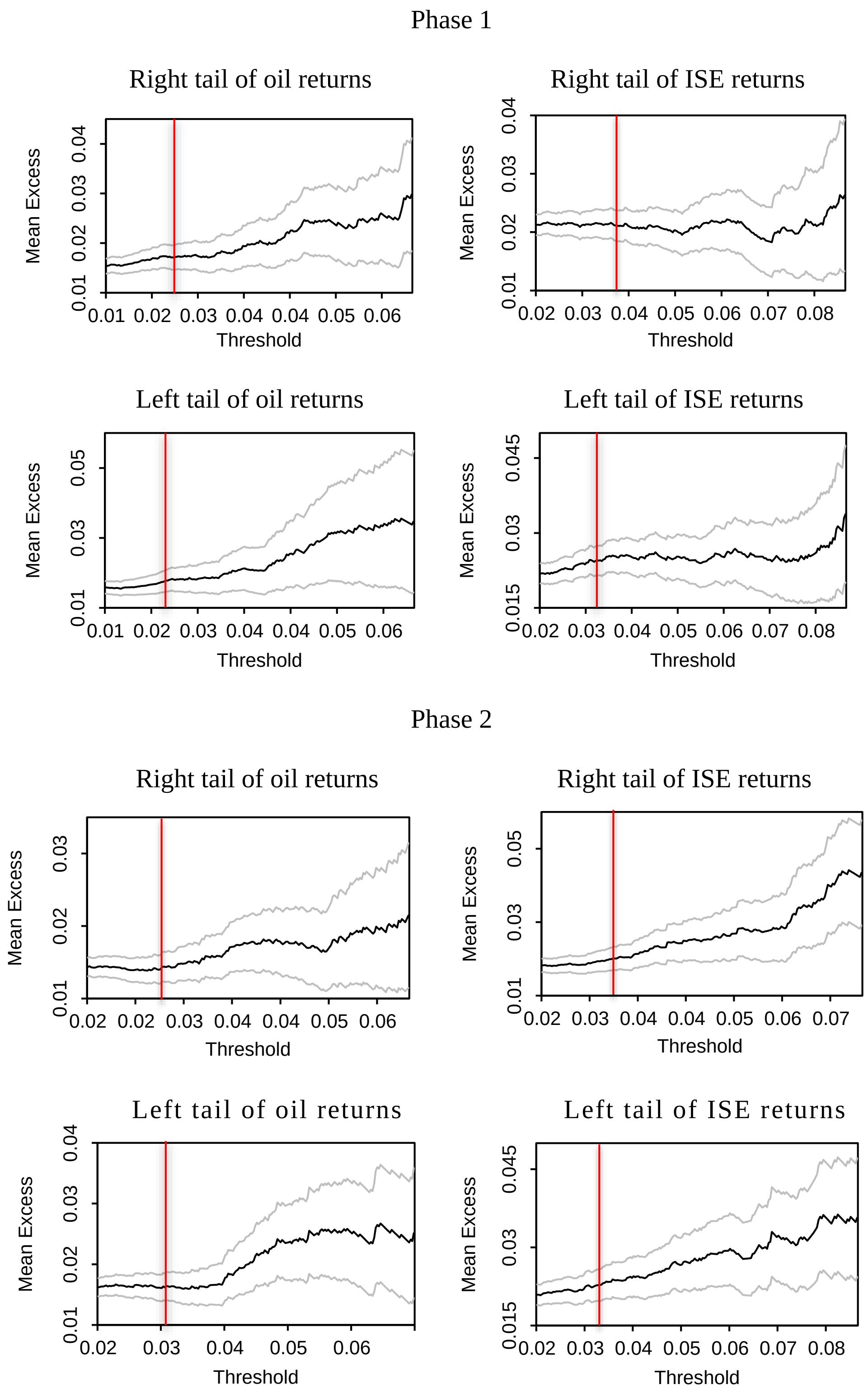


Figure 8. Mean residual life plots

The figure represents Mean Residual Life plots for the left and right tails of oil returns and ISE 100 returns. The figure shows how mean value of exceedances over the threshold changes with different choices of thresholds. For each threshold level, the estimated mean residual life value is plotted within a 95% confidence interval. The thresholds selected are marked with the longitudinal vertical lines that correspond to ninetieth quantile for the right tails and tenth quantile for the left tails. The mean excess values against threshold levels are expected to be linear after an appropriate threshold level.

Figure 6 and Figure 7 presents threshold choice plots for the left and right tail of oil returns and ISE 100 returns, for the shape and scale parameters respectively. Figures show how the estimated shape and scale parameter changes with different threshold choices. Estimated parameters are plotted within a 95% confidence interval for each threshold level. Longitudinal vertical lines show selected thresholds and estimated shape parameters are expected to be constants after selected thresholds. Figure 8 presents Mean Residual Life plots for the same data set and shows how mean value of exceedances over the threshold changes with different threshold choices. Longitudinal vertical lines shows the threshold selection and mean excess values against threshold levels are expected to be linear after an appropriate threshold level.

The dependence strength between extreme returns of ISE and oil prices is estimated by fitting joint exceedances to a bivariate extreme value distribution. Censored likelihood methodology is used for this procedure, which is described in Ledford and Tawn's (1996) study.

Dependence structure of extreme returns is computed by using logistic bivariate Generalized Pareto Distribution (GPD) model. Picklands (1975) studies GPD model in his work and is followed by Smith (1987) and Leadbetter (1991). This model is also described in Mendes and Moretti (2002), Klüppelberg (2006) and Onay and Ünal (2011). Tools for computing logistic bivariate GPD model are provided in Ribatet's (2009) Peak Over Threshold (POT) package. Summary of the model is presented below.

Following dependence function defines the logistic model:

$$A : [0,1] \rightarrow [0,1] , \quad w \mapsto \left\{(1-w)^{1/a} + w^{1/a}\right\}^{a} \qquad (1)$$

where $0 < \alpha \leq 1$. This gives the joint distribution function:

$$G(x,y) = e^{-V(x,y)} = e^{-\left(x^{-1/a}+y^{-1/a}\right)^{a}} \qquad (2)$$

for $x, y > 0$. Complete dependence is obtained when $\alpha \rightarrow 0$ and total independence is when $\alpha = 1$.

De Carvalho and Ramos (2012) explain the dual measures of Chi and Chi bar statistics concisely in analysis of extremal dependency.

$$x = \lim_{u\to\infty} pr(X > u \mid Y > u) = \lim_{p\uparrow 1} pr\{X > F_X^{-1}(q) \mid Y > F_Y^{-1}(q)\}$$

Chi statistic takes values in [0, 1], and this statistic can be used to assess the degree of dependence that remains in the limit where u is a high threshold (Coles et al., 1999; Poon et al., 2004).

If dependence persists as $u \rightarrow \infty$, then $0 < x \leq 1$ and X and Y are said to be asymptotically dependent; otherwise, the degree of dependence vanishes in the limit, so that $x = 0$ and the variables are asymptotically independent.

To measure extremal dependence under asymptotic independence, Coles et al. (1999) introduced another measure, Chi Bar statistic, which takes values on the interval [−1, 1].

$$\overline{x} = \lim_{u\to\infty} \frac{2 \log pr(X > u)}{\log pr(X > u, Y > u)} - 1$$

A Chi Bar Statistic exactly equal to one implies asymptotic dependence, whereas chi bar statistics that are in the interval [-1,1] imply asymptotic independence. The interpretation of Chi Bar is rather parallel to that of the Pearson correlation, such that positive (negative) Chi Bar statistics imply positive (negative) association and zero Chi bar statistics implies exact independence in the extremes.

Hence joint tail dependence can be explained by chi and chi bar statistic measures together. If Chi Bar = 1 and 0 < Chi ≤ 1, then the variables are asymptotically dependent and Chi assesses the degree of dependence within the class of asymptotically dependent distributions. However, if −1 < Chi Bar < 1 and Chi = 0, then the variables are asymptotically independent and Chi Bar assesses the degree of dependence within the class of asymptotically independent distributions.

CHAPTER 4

EMPRICAL RESULTS

Threshold levels of tenth and ninetieth quantiles of oil returns and ISE 100 returns indicates that there are 299 highest and 299 lowest extreme events exceeding selected thresholds out of 2989 daily returns for each phase. The corresponding quantiles taken as thresholds for the analysis of extreme ISE returns are -3.52% for the left tail and 3.77% for the right tail in the first phase studied. In the second phase, the thresholds are -3.17% and 3.05% for the left and right tails, respectively. For Brent oil returns, tenth and ninetieth quantiles are respectively -2.38% and 2.37% in the first phase and -2.80% and 2.68% in the second period. For example, if there is a daily loss greater than 3.52% in the first phase studied, the observation is considered to exceed the threshold and is incorporated in the estimation of the GPD model for the left tail. Similarly, if there is a daily return higher than 3.77% in the first phase, the observation is included in the estimation of the model for the right tail.

Table 3 shows bivariate EVT model results for ISE100 and Brent oil extreme returns. Independence assumption suggests that average 29.9 events would coincide on the same day at tenth and ninetieth quantiles. In the period between 1988 and 2000, our results show that 37 of the 299 highest returns and 29 of the lowest 299 returns happen on the same day. However, in the period between 2000 and 2012, we observe higher number of joint exceedances, as 49 highest returns and 61 lowest returns happen on the same day. In other words, for example there are 61 days when ISE lost more than 3.17% and Brent oil lost more than 2.80% concurrently.

Table 3 also shows us figures for computing conditional probabilities to investigate oil price latency effect to stock markets by setting a 3-day margin. Under total independence assumption, for each consecutive day 29.9 extreme observations, or a total of 89.7 extreme observations over the next three days is expected. This thesis shows that 105 of the 299 highest returns (35%) and 91 of the lowest 299 returns (30%) happen within the 3 days at the first phase, while 121 of the 299 highest returns (40%) and 138 of the lowest 299 returns (46%) happens within the 3 days at the second phase respectively. The numbers in parentheses imply conditional probabilities of having an extreme daily stock market return in the coming next three days when today is an extreme day for oil returns. Given that oil loses more than 2.80% one day in the second sub-period, there is 46% probability that in the next three days ISE experiences a daily loss greater than 3.17%.

Table 3. Bivariate Extreme Model Results for ISE100 and Brent Returns

	Phase 1 (1988 - 2000)		Phase 2 (2000 - 2012)	
	Right Tail	Left Tail	Right Tail	Left Tail
Chi-Statistic	0.023	0.001	0.066	0.116
Deviance	329	434	153	305
Marginal Number Above	299	299	299	299
Joint Number Above	37	29	49	61
Joint Number Above (3days)	105	91	121	138

This table shows the results of the bivariate extreme value models forecasted for Brent oil and ISE 100 extreme returns. The right and the left tail models show results for extreme high returns and extreme high losses returns at ninetieth quantile respectively. The analysis is carried for two sub-periods, where phase 1 corresponds to the period between 1988 and 2000 and phase 2 to the period between 2000 and 2012.

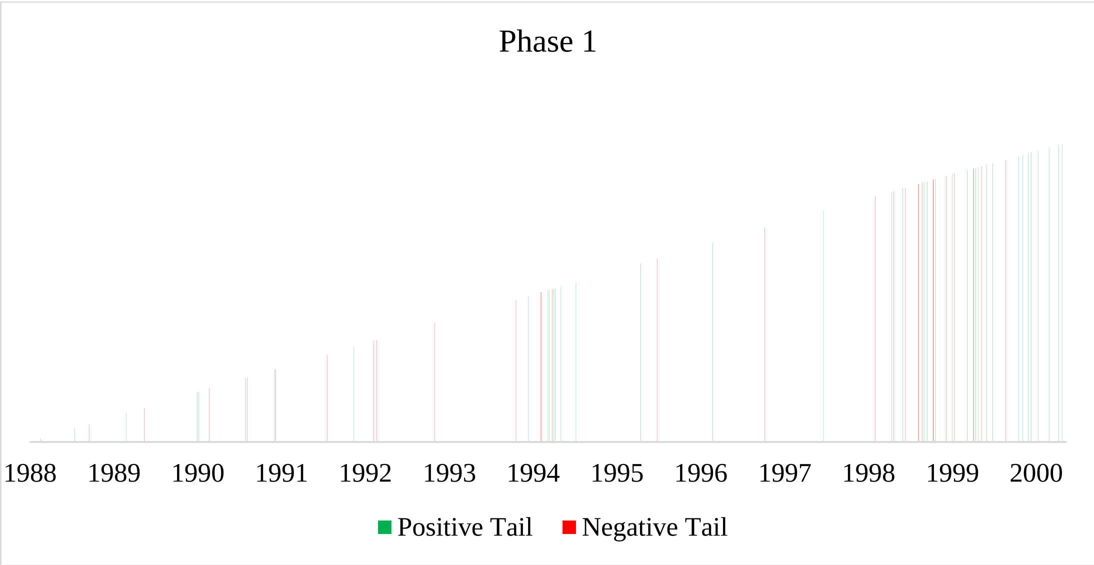
Table 4 shows the estimated parameters and their standard errors of the GPD models that are fit to our exceedance data over selected thresholds. Except for the second shape parameters for right and left tails in the phase 1, all estimated parameters are significant. The alpha parameters of all four models estimated (for both sub periods and for both right and left tails) are close to one, which imply independence in extreme observations. These results are in line with chi-statistic values reported in Table 3, which also imply independence with close to zero values.

Table 4. Bivariate Extreme Model Estimates for ISE100 and Brent Returns

	Phase 1 (1988 - 1999)		Phase 2 (1999 - 2011)	
	Right Tail	Left Tail	Right Tail	Left Tail
Scale1	0.0142*** (0.0012)	0.0141*** (0.0012)	0.0120*** (0.0000)	0.0136*** (0.0011)
Shape1	0.1662*** (0.0624)	0.2238*** (0.0698)	0.1804*** (0.0511)	0.1872*** (0.0631)
Scale2	0.0202*** (0.0015)	0.0243*** (0.0021)	0.0143*** (0.0013)	0.0188*** (0.0016)
Shape2	0.0512 (0.0509)	0.0750 (0.0655)	0.2922*** (0.0737)	0.1853*** (0.0700)
Alpha	0.9830*** (0.0119)	0.9992*** (0.0000)	0.9518*** (0.0157)	0.9134*** (0.0175)

This table shows the estimated parameters of the GPD models fit using bivariate data series ISE 100 and Brent oil returns at ninetieth quantile. The numbers in parentheses gives standard errors of the estimated parameters. The analysis is carried for two sub-periods, where phase 1 corresponds to 1998 and 2000 and phase 2 to the period between 2000 and 2012. ***, **, * Denote significance at the 1%, 5%, and 10% levels, respectively.

Figure 9 shows the distribution of extreme coinciding days for both phases. As bivariate extreme model results also indicate, increase in the joint number of days exceeding selected threshold levels in the second phase can be clearly seen in Figure 9. Interestingly, coinciding days of extreme value analysis pile at the period between 2008 and 2012 in the second phase, which also overlaps with the recent global crisis period. 33 events for positive tail and 44 events for negative tail occurred within 2008-2012 period.



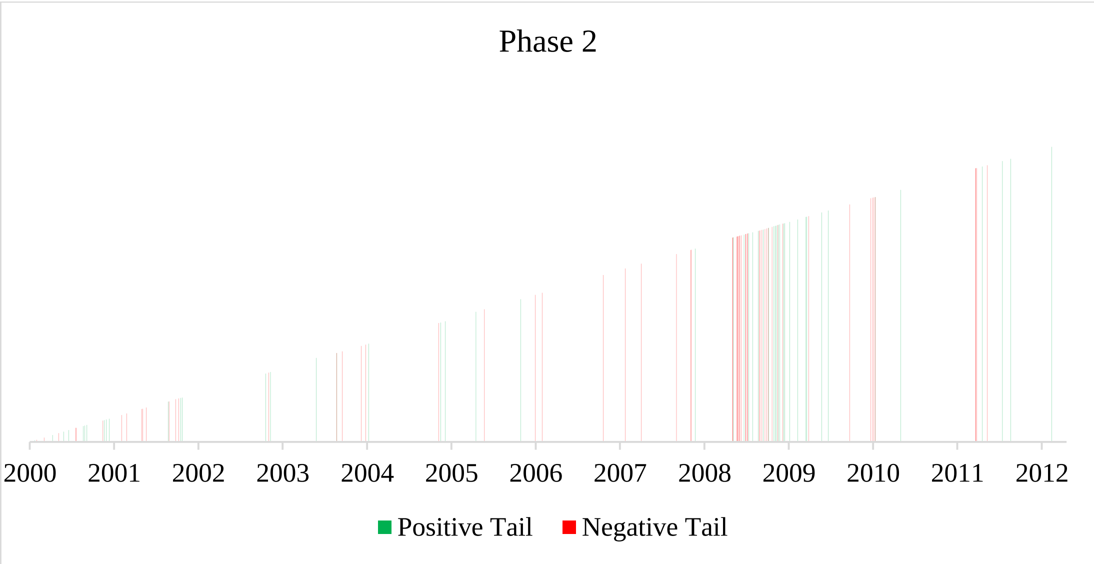


Figure 9. Distribution of extreme coinciding days

The figure represents distribution of extreme coinciding days of oil returns and ISE 100 returns. Green vertical lines show coinciding days of right tail of the distribution and red vertical lines show coinciding days of left tail of the distribution. Vertical lines do not indicate any scale, they are plotted when joint extremes are observed for oil and stock market concurrently. Phase 1 and phase 2 cover the periods from 1988 to 2000 and from 2000 to 2012, respectively. In each phase 2989 daily observations are used.

A more focused analysis of bivariate EVT for the 2008-2012 period is represented in Table 5. Bivariate EVT model results, the estimated parameters and their standard errors of the GPD models is included in the Table 5. All estimated parameters are statistically significant. Chi values are significantly higher for the 2008-2012 period compared the 2 phases analyzed in the thesis, which are 0.209 and 0.317 for the right and the left tail respectively. Moreover, under independence assumption, extremes over tenth and ninetieth quantiles are expected to be observed simultaneously on the same day 11.3 times on average. Our results show that 33 of the 113 highest returns and 44 of the 113 lowest returns happen on the same day for the ISE 100 index and Brent oil returns.

Table 5. Bivariate Extreme Model Results for ISE100 and Brent Returns 2008 - 2012

	Model Results			Model Estimates	
	Right Tail	Left Tail		Right Tail	Left Tail
Chi-Statistic	0.209	0.317	Scale 1	0.0107*** (0.000)	0.0133*** (0.0019)
Deviance	-11	11	Shape 1	0.4158*** (0.1092)	0.2718*** (0.1098)
Marginal Number Above	113	113	Scale 2	0.0118*** (0.000)	0.0168*** (0.0025)
Joint Number Above	33	44	Shape 2	0.2773*** (0.0866)	0.1769* (0.1195)
			Alpha	0.8411*** (0.0321)	0.7511*** (0.0353)

This table shows the results of the bivariate extreme value models forecasted for Brent oil and ISE 100 extreme returns and the parameters of the GPD models fits. The right and the left tail models show results for extreme high returns and extreme high losses returns at ninetieth quantile respectively. The analysis is carried for the period between 2008 and 2012.

Figure 10, Figure 11 and Figure 12 show chi and chi-bar plots of bivariate extremes studied for the periods between 1988-2000, 2000-2012 and 2008-2012, respectively. The plots show how chi and chi-bar values change on the vertical axis, as higher and higher thresholds are taken on the horizontal axis. For asymptotic independence chi-statistics are expected to approach to zero and chi-bar statistics show the degree of dependence. Chi values are fluctuates around 0 for the phase 1 and phase 2 period studied. For the 2008-2012 period, chi values are around 0.2-0.4. Degree of dependence is hence observed in the chi bar plots. Chi bar plots show stronger relationship between oil price and ISE 100 index in the 2008-2012 period compared to phase1 and phase 2 periods.

Phase 1 (1988-2000)

Right tail of ISE 100 and oil returns

Left tail of ISE 100 and oil returns

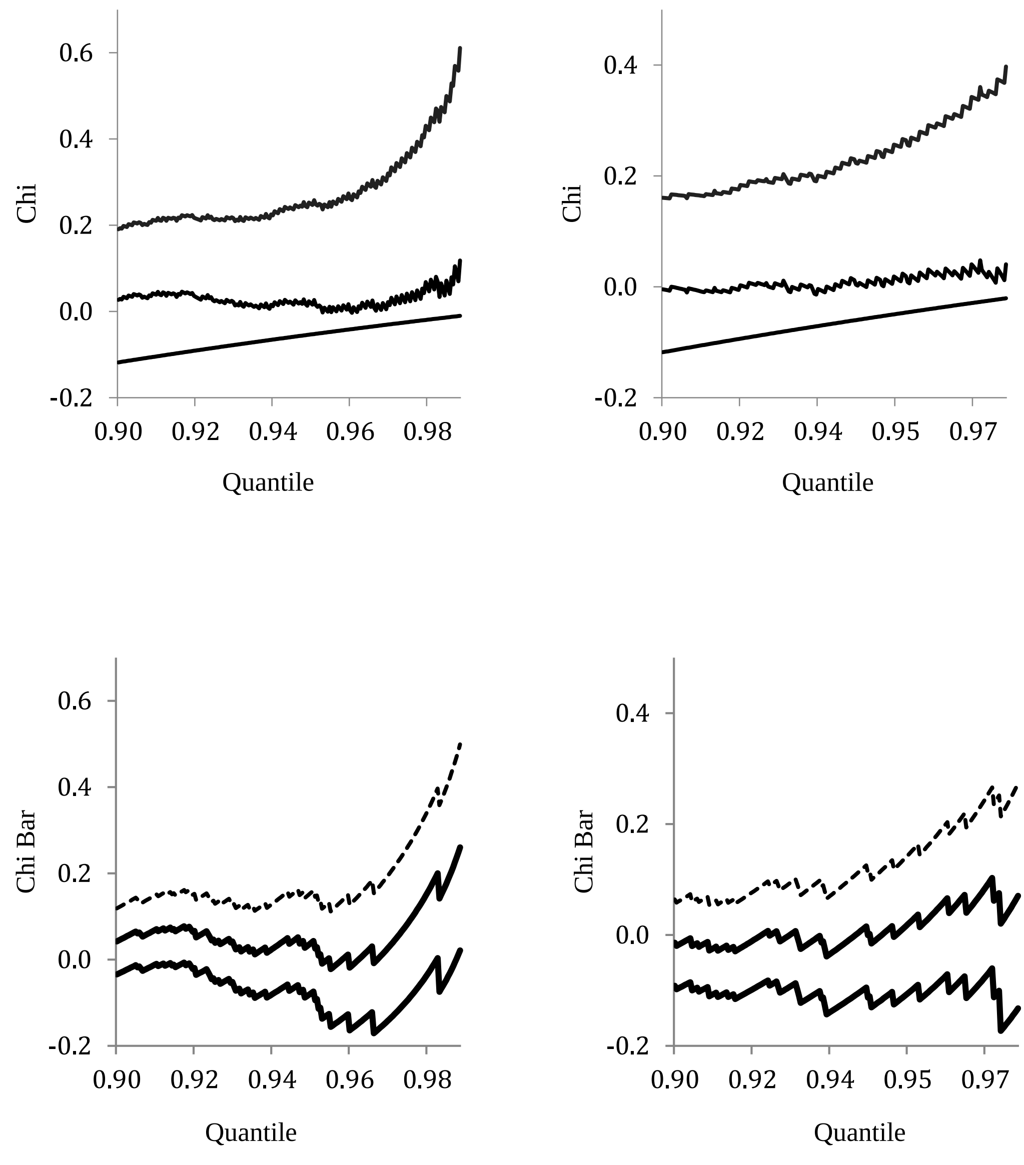


Figure 10. Chi and chi-bar plots 1988 – 2000

The figure presents chi and chi bar plots for the left and right tails of oil returns and ISE 100 index. Chi and Chi-Bar plots show the chi-statistics of each bivariate series for both left and right tails at 90% confidence. Extremes that exceed the quantile level on the horizontal axis are used in estimating the chi-statistics. Higher thresholds are taken as we go right on the horizontal axis. For asymptotic independence chi-statistics are expected to approach to zero and chi-bar statistics show the degree of dependence.

Phase 2 (2000 - 2012)

Right tail of ISE 100 and oil returns | Left tail of ISE 100 and oil returns

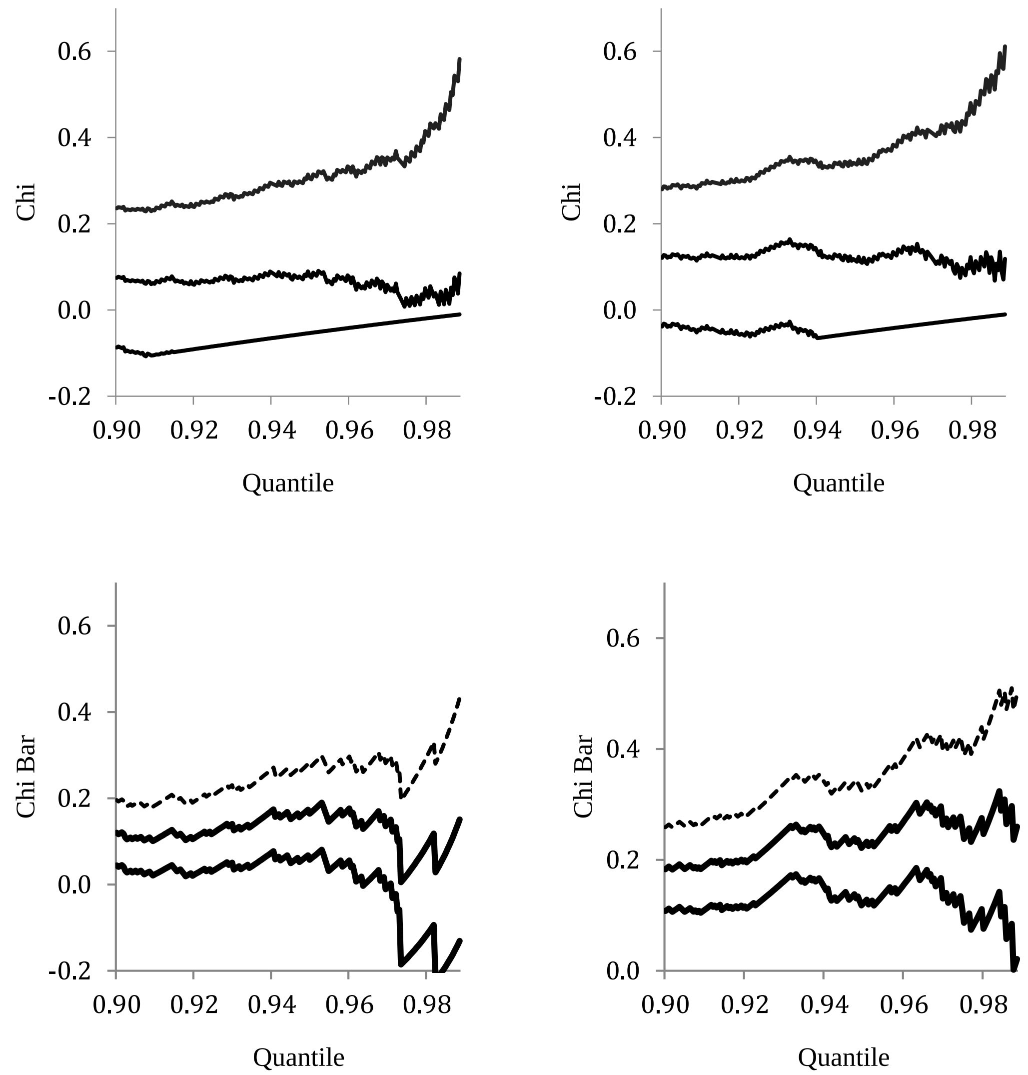


Figure 11. Chi and chi-bar plots 2000 - 2012

The figure presents chi and chi bar plots for the left and right tails of oil returns and ISE 100 index. Chi and Chi-Bar plots show the chi-statistics of each bivariate series for both left and right tails at 90% confidence. Extremes that exceed the quantile level on the horizontal axis are used in estimating the chi-statistics. Higher thresholds are taken as we go right on the horizontal axis. For asymptotic independence chi-statistics are expected to approach to zero and chi-bar statistics show the degree of dependence.

2008 – 2012 Period

Right tail of ISE 100 and oil returns | Left tail of ISE 100 and oil returns

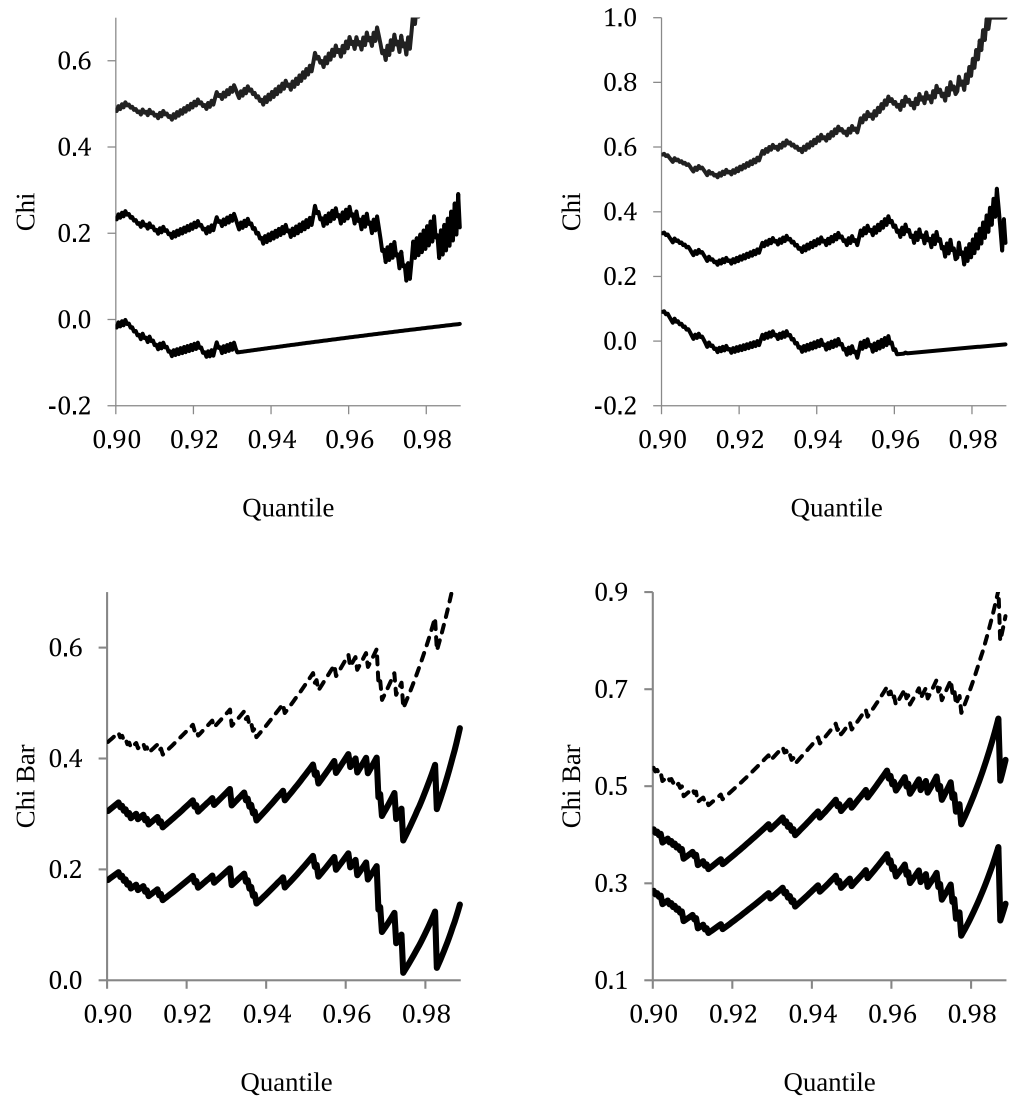


Figure 12. Chi and chi-bar plots 2008 - 2012

The figure presents chi and chi bar plots for the left and right tails of oil returns and ISE 100 index. Chi and Chi-Bar plots show the chi-statistics of each bivariate series for both left and right tails at 90% confidence. Extremes that exceed the quantile level on the horizontal axis are used in estimating the chi-statistics. Higher thresholds are taken as we go right on the horizontal axis. For asymptotic independence chi-statistics are expected to approach to zero and chi-bar statistics show the degree of dependence.

In general, it is not possible to speak of a total dependency relationship between oil and ISE index. However, bivariate extreme dependence analysis indicates that Brent oil and ISE 100 returns have higher dependence at the second phase, in the years from 2000 to 2012. Joint number of days exceeding selected thresholds at second phase is increased by 32 percent for the positive tail (from 37 days to 49 days) and by 110 percent for the negative tail (from 29 days to 61 days) compared to the first phase. Chi-statistics at the second phase is 2.7 times greater for the positive tail compared to the first phase, which is 0.023 in the first phase and 0.066 in the second phase. For the negative tail, it is 116 times greater compared to the first phase, which is 0.001 in the first phase and 0.116 in the second phase. 2008-2012 period is analyzed separately within the thesis in view of Figure 9. Chi statistics and joint number of days is considerably higher compared to the overall analysis of the dataset. In the light of model results, increase in the oil and ISE 100 returns extreme dependence during the second phase is clearly mentioned together with excess increase in 2008-2012 period. Negative returns for oil and ISE 100 index have higher dependence value compared to the positive returns at the second phase and 2008-2012 period. It is possible to refer that negative oil price movements affect ISE 100 index more commonly compared to positive movements at the second phase.

CHAPTER 5

CONCLUSION

This thesis examines extreme dependence between oil prices and Turkish stock index. The data used for dependence analysis consist of daily log returns on Brent oil prices and ISE 100 index for the period between 1988 and 2012. Turkey is an emerging country that supplies nearly half of its energy requirement from crude oil. Oil is one of the major commodities for Turkey's total imports. Expanding emerging countries need oil as a source of energy for their growing industries. Their exposure to oil price fluctuations is more directly compared to developed nations. Main motive of this thesis is to show oil price effect in an oil dependent emerging country, such as Turkey. Researches that investigate oil price and stock market relationship in the literature, mainly focus on analyzing central observations. This thesis brings a novel approach to analyze the dependency relationship of stock exchange and oil returns by exploring the extreme observations employing bivariate EVT models.

Results of this thesis reveal an asymptotic independence between oil prices and ISE 100 index returns in extreme observations. Bivariate extreme dependence analysis applied to the data set by dividing data into two phases, where phase 1 and phase 2 cover the periods from 1988 to 2000 and from 2000 to 2012. In the first phase studied, the chi-statistics are very close to zero (0.023 and 0.001 for the left and right tails respectively), implying no dependence at all. In the second phase, the extreme observations chi-statistics are somewhat higher but still very close to zero (0.066 and 0.116 for the left and right tails respectively). Moreover, 2008-2012 period is analyzed separately within the thesis, to assess the recent crisis effect to the oil price and stock market relationship. During this period, chi values are much higher (0.209 and 0.317 for the left and right tails respectively) compared to the overall data analyses. Out of 25 years of data studied, 35.2 percent of the joint extreme events for ISE 100 index and oil returns are observed within this 5 year period. Extreme dependence analysis indicates that oil and ISE 100 returns have higher dependence at the second phase compared to first phase, and overall highest dependence is found in 2008-2012 period. It is also observed that negative oil price movements affect ISE 100 index more commonly compared to positive movements at the second phase and in the 2008-2012 period. Oil price effect latency to stock markets is also examined within the thesis by setting a 3-day margin. Yet, the number of observed joint exceedances is quite close to the expected values under complete independence assumption.

Findings of this thesis may help investors, financial analysts, policy makers, portfolio managers and risk managers to have a better understanding of the market, as it considers extreme observations. On the firm level, companies should be able to adapt to the recent oil price market regime where extremes are more common. On the other hand, the findings of the thesis suggest that Turkish government policy makers should pay special attention on oil market shocks as these shocks not only affect country's current account deficits but also overall economy which is observed through national stock market movements.

Our findings may also help to identify better diversification opportunities. We emphasize two main points among our results for diversification process. First, there is higher dependence of stock markets and extreme oil price movements during global crisis period. Second, extreme negative oil price shocks affect stock markets more compared to extreme positive shocks. For risk analysis, practitioners are more concerned about the extreme observations on the left tail as huge losses on these days can have devastating results. Given these findings, decision makers should consider increasing dependency of oil and stock markets and develop their diversification strategies in line with the positive association observed in the extreme observations.

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