

## MSc in Energy \& Finance

## Stock Markets \& Oil Price Risk: The case of Developed Countries

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#### Abstract

The purpose of this paper is to study the impact of oil and energy price changes on a set of Developed as well as Emerging Stock Market returns. This study employs an international multi-factor model which allows for both unconditional and conditional risk factors, and it's contribution to the literature is the fact that we use the modified framework proposed by Kilian (2008a), in which we decompose oil price changes into three components, namely oil-supply shocks, global oil-demand shocks, and oil-market specific shocks, in order to investigate the relationship between oil price risk and the returns of various Stock Markets. Furthermore, this paper is meant to shed light on the possible asymmetric impact of risk between emerging and developed markets.


Keywords: Global Stock Markets; Oil Price Risk; Energy Price Risk; International Multi-Factor Model;

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## 1. Introduction

While today's world energy mix is changing with the transition towards a higher penetration of renewables, oil still remains and will continue to remain one of the most important energy commodities. The world economy is influenced by oil price changes, and it was Hamilton (1983) that demonstrated that the oil market was responsible for all U.S. recessions post-World War II but one.

Since then, lots of studies have been performed on the effect of oil price changes on economic activity, on employment, and a whole range of other macroeconomic variables (Gisser \& Goodwin, 1986; Ferderer, 1996; Raymond \& Rich, 1997; Hamilton, 2003; Bachmeier, 2008; Lee \& Ning, 2017, among others). A vast literature exists nowadays also on the effect of oil and energy price shocks on the financial markets, too, with the majority of the papers, though, focusing on developed markets only (Chen et al., 1986; Jones \& Kaul, 1996; Sadorsky, 1999; Papapetrou, 2001; Sadorsky, 2001; Basher \& Sadorsky, 2006; Park \& Ratti, 2007; Apergis \& Miller, 2008; Kilian \& Park, 2009; Asteriou \& Bashmakova, 2013; Cunado \& Garcia, 2013; Broadstock \& Filis, 2014; Gunter, 2014; Kang et al., 2014; Gupta, 2016, among others).

While it's generally accepted that the changes in the price of oil are important factors in understanding the fluctuations of financial markets, there is still a large debate over the theoretical relationship between stock returns and oil prices. Chen et al. (1986) presented evidence that oil prices don't affect stock prices, while other researchers such as Jones and Kaul (1996) argued that there is a negative relationship between stock returns and oil prices. According to the cash flow hypothesis (Fisher, 1930; Williams, 1938), the value of an asset is determined by the expected discounted cash flows. Since oil is such an important input in most sectors of the global economy, it stands to reasons that higher prices of oil will lead to higher costs of production, thus reducing the future cash flows (dividends), which will lead to lower stock returns. Furthermore, rising oil prices will also lead to higher nominal interest rates (Smyth \& Narayan, 2018). These interest rates, though, are used to discount the value of the future cash flows, so higher interest rates will also lead to lower stock returns.

However, according to Kilian (2008a), the stock returns may be impacted either negatively or positively due to increases of oil price, depending on the cause of the oil price shock. For example, if the oil prices were to rise due to an economic expansion, it's very probable that the stock returns would be impacted positively, which is why according to Kilian, it's important to decompose the oil price risk into its various components.

The models that are employed in the literature also vary greatly, ranging from multi-factor models estimated with OLS, to Panel Data estimations, as well as Vector Autoregressive Models which account for the different types of oil price shocks.

This paper aims to contribute to the literature by employing an international multi-factor model such as the one used by Sadorsky, only it's also going to include different types of oil shocks as variables instead of only including crude oil prices. Furthermore, we are going to try to ascertain whether there is an asymmetry between the emerging and developed countries by including both of them in our models.

The rest of this paper proceeds as follows: in Section 2 previous studies -some of which were already mentioned in Section 1- on the effects of oil price changes on the returns of stock markets are presented in more detail. In Section 3, the Data are presented with their sources, descriptive statistics as well as transformations that were performed. This part is followed by the presentation of the various models and methodology that were used in this paper in Section 4. In Section 5, the empirical results of this paper are presented. Finally, in Section 6, there is a short summary of the findings of this paper, followed by recommendations for what future studies can be performed in this subject.

## 2. Literature Review

### 2.1. Relationship between Stock Returns \& Oil Prices

The interrelation between oil price risk and the financial markets, as well as with a series of macroeconomic variables such as employment, economic activity has been studied by many researchers. It was Hamilton (1983) who first researched the impact of higher oil prices on a set of macroeconomic factors. In his pioneering paper, using Granger Causality, he demonstrated that the oil market was responsible for almost all U.S. recessions post-World War II but one (1949-1972), and that the economic turndown occurred approximately nine months after the oil price increases. It's worth noting, though, that this relationship ceased to exist after 1973.

Many of the early papers in the literature dealt with ascertaining the relationship between stock returns and changes in the price of crude oil. Chen et al (1986) continued in Hamilton's steps, only this time he studied the impact of macroeconomic variables on a set of stock returns, employing twenty years of monthly data. While they ascertained that interest rates, inflation rates, and bond yields affect the stock market, they uncovered no evidence that oil price was priced in the stock market. The same result was reached by Hamao (1989), who used the same framework as Chen et al., but this time on a set of Japanese stocks.

Jones and Kaul (1996) tested whether international stock markets (Canada, U.S., United Kingdom, and Japan) react to oil shocks using quarterly data, and whether this reaction is justified by current and future changes in real cash flows (Cash Flow Hypothesis). As a proxy for oil prices, they used a Producer Price Index for Fuels. Their models did find a significant negative relationship between oil prices and stock market returns for the American and Canadian Stock markets, but their findings for the Japanese and British stock market weren't significant.

When Huang et al. (1996) studied the relationship between the oil futures market and the U.S. daily stock returns, using daily oil future returns instead of physical oil returns, his results differed. By employing a Vector Autoregression model (VAR), they found that oil futures returns don't
have a significant impact on the S\&P 500 index, although they did influence certain oil company stock returns.

This negative relationship uncovered by Jones and Kaul, was further supported by Faff and Brailsford (1999) who investigated the sensitivity of equity returns to an oil price shock for the Australian industry, using a multi-factor model and monthly data for the time period 1983-1996.

Sadorsky (1999) also employed a Vector Autoregression model (VAR) to examine the links between oil price changes and real stock returns for the U.S., but used a monthly frequency data set of four variables (industrial production, interest rates, real oil prices, and real stock returns) covering the period 1947-1996. In his findings, he ascertained that real stock returns are affected negatively by oil price changes and oil price volatility. Also, he found evidence of asymmetry in how oil price volatility shocks affects the stock returns. More precisely, positive oil price shocks have a greater impact on stock returns than negative oil price shocks.

This was also supported by earlier research, such as that of Mork (1989), who showed that while increases in the price of oil had a significant negative impact on GNP, when the prices of oil decreased that didn't have the opposite effect. Ferderer (1996) also reached similar results for the U.S., while Lee et al. (2001) documented the same for Japan. Although in papers that deal with certain oil-exporting oil-producing countries such as U.S. or Norway (Sadorsky, 1999; Bjornland, 2009) it has been showed that there is evidence of asymmetry, the same doesn't apply for European countries. Park and Ratti (2008), who investigated oil price shocks and stock returns for the U.S. and 13 European countries, showed that positive and negative oil price shocks had no asymmetric effects on the real stock returns of the 13 European countries. This is further evidence that it's important to examine the effects of oil price shocks on stock returns on a country by country basis. The national real oil price can be obtained by using the foreign exchange rate as well as the Consumer Price Index of each country to transform the U.S. price of oil.

Papapetrou (2001) used a multivariate vector-autoregression (VAR) approach, to explore the dynamic relationship between real stock prices, oil prices, interest rates, real economic activity, and employment in Greece. Her empirical results, using a monthly frequency data set over the period

1989-1999, showed that oil prices do indeed explain stock price movements, and that positive oil price shocks also have a negative relationship with real stock returns.

It was Sadorsky (2006) that investigated the relationship of oil price changes and emerging stock market returns, by using an international multi-factor model that incorporated both unconditional as well as conditional risk factors. The estimated models used daily, weekly, as well as monthly frequency data, with variables such as market risk, oil price risk, exchange rate risk, while including also risk metrics such total risk, skewness and kurtosis. His results showed that stock market returns are very sensitive to oil price risk. More specifically, they noted that "emerging economies tend to be more energy intensive than more advanced economies and therefore more exposed to higher oil prices".

It's worth noting, though, that the sign of the relationship between oil returns and stock returns changed depending on the frequency of the data that were used. When employing daily data, crude oil price increases impacted positively the stock returns, but when the researchers used weekly and monthly data, the stock returns were impacted negatively by crude oil price increases.

It's also important to highlight here that most of the literature doesn't include higher statistical order moments, although there have been studies which have showed that investors actually care about more than just the mean of their stock returns. Studies such as the ones performed by Shapiro (2003) and Bekaert and Harvey (1995) have shown that especially in the case of emerging market, total risk which is measured as the variance of market returns, is an important variable to include in the models. Harvey and Siddique (2000) proposed that skewness is also an important risk metric to include in the models and that there is a negative relationship between skewness and returns, while Bekaert and Harvey (1997) suggested that kurtosis might also be important. The negative relationship between conditional skewness and returns was further supported by Bali et al. (2011) and Chang et al. (2013). When using higher moments, though, it's important to note that to avoid problem of Multicollinearity one shouldn't include total risk, skewness and kurtosis in the same model simultaneously.

Another important contribution to the literature, in regards to including higher statistical order moments, was the one performed by Mo et al. (2019). They estimated a multi-factor model to
study the impact of skewness of oil returns on stock returns for China using monthly data, and also including control variables such as leverage, market-to-book ratio, return on assets (ROA), and turnover ratio. They concluded that there is a negative relationship between the skewness of oil returns and stock returns but only when the market is falling.

Following in Sadorsky's steps, and employing his framework, Nandha and Hammoudeh (2006), studied the links between domestic beta risk and stock returns in the Asia-Pacific region, controlling for oil and exchange rates. This paper contributed also to the literature as they highlighted the importance of using domestic currency when measuring oil prices in order to capture the sensitivity of each country's stock market to oil shocks.

Hammoudeh and Eleisa (2008) employed a Vector Error Correction Model (VECM) approach to investigate the relationships of stock markets of the Gulf Cooperation Council (GCC) and the New York Mercantile Exchange oil futures prices. For their approach, they used daily data, and their results showed that out of the six stock markets (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates) that make up GCC, only the stock market of Saudi Arabia exhibited a bi-directional relationship between stock oil prices and stock prices.

Sadorsky's framework was also employed by Asteriou and Bashmakova (2013), and their contribution to the literature was that they studied the impact of oil returns on a different set of emerging stock markets such as Czech Republic, Estonia, Hungary, Lithuania, and Latvia among others. Their dataset included daily data for the various stock markets of the countries, the MSCI World Index which is designed to measure global development market equity performance, the Trade Weighted Exchange Index which is a weighted average of the foreign exchange value of the U.S. dollar against other currencies, the WTI returns, as well as risk metrics. In their various models, the oil betas and the risk factors were significant, with the oil betas being negative when markets were down, as expected. The overall results suggested that oil price changes are especially significant when dealing with emerging stock returns.

While the majority of the papers in the literature have indicated that there is a negative link between stock returns and oil price changes, there have also been studies that have unveiled a positive relationship. Narayan and Narayan (2009), when modelling the impact of oil price changes on

Vietnam's stock prices using daily data, concluded that there is positive long-run cointegrating relationship between stock prices, oil prices and exchange rates. Silvapulle et al. (2017), who also studied the impact of oil price changes on the stock market indices of 10 large oil-importing countries, contributed to the literature by allowing for a common trend function to evolve across all countries, and they also reached the result that there is a positive relationship between oil price changes and stock market indexed.

Of course, there have also been other studies that discovered no link between stock returns and oil price changes. Cong et al. (2008), employing a Vector Autoregressive Model (VAR) to study the impact of oil price shocks on Chinese stock returns, unveiled that there was no significant relationship. A similar result was reached by Miller and Ratti (2009), who used a Vector Error Correction Model (VECM) to study the long-run relationship of six OECD countries. While he discovered a significant negative relationship that lasted for over a decade from 1971-1980, that relationship disappeared after 1980, before appearing again from 1988-1999, suggesting the existence of oil price bubbles.

There are a few reasons that the literature doesn't seem to agree on the exact relationship between oil price changes and stock market returns. First of all, as Hamilton (2009a) pointed out, investors up till the Global Financial Crisis associated the increased prices of oil with an expanding and growing economy. Also, as Mollick and Assefa (2013) so eloquently put, a stock market index is comprised of many firms, some of which may stand to benefit from an oil fluctuation while other stand to lose, so there is no reason why all the stock indexes across the various countries should behave the same. Another possible reason according to Smyth and Narayan (2018) is due to how differently the various firms that compose each country's stock market index depend on oil.

### 2.2. Relationship between Stock Returns \& Oil Prices across Sectors

Of course, it's important to note that despite the fact that the literature doesn't seems to agree on whether or not there is a negative relationship between stock returns and positive oil price shocks,
there is something that many researchers agree on, and that is that not all the sectors react the same to oil price increases. It's worth noting here that there is a vast literature on the relationship between oil price shocks and stocks of specific sectors.

As El-Sharif et al. (2005) showed when they researched the relationship between the price of crude oil and the oil and gas sector in the United Kingdom, using a multi-factor model and daily data, certain stock returns are bound to increase. According to their empirical results, oil and gas stock returns are impacted by changes in the price of crude oil as well by the exchange rates, but where the price of crude oil is concerned, there is a positive relationship as an increase in the prices of crude oil led to increases in the returns of oil and gas stocks. This was also supported by earlier findings of Sadorsky (2001), who also estimated a multi-factor model using monthly data, and discovered a positive relationship but for the Canadian Oil and Gas sector.

Nandha and Faff (2008) found that the returns of manufacturing companies are negatively impacted by positive increase of oil price. This was further supported by Narayan and Sharma (2011), who used GARCH models to examine relationship between oil prices and specific stock returns, and concluded that stocks in sectors such as Transportation, Real Estate, Manufacturing, Chemical and Medical are negatively impacted in response to positive oil price shocks, whereas Energy stocks are positively impacted by positive shocks in the price of crude oil.

Elyasiani et al. (2011), using also GARCH models for 13 U.S. industries, also concluded that stock returns of oil related industries or renewable energy industries are positively affected by the increase of crude oil prices, whereas stock returns in oil-users industries are negatively impacted by the rise of crude oil prices. They also concluded that oil-user industries are more likely to be heavily impacted by changes in the volatility of oil returns, than changes in the oil returns.

Aggarwal et al. (2012) further supported the earlier results of Narayan and Sharma, as they showed that the returns of firms in the transportation sector are negatively affected by increases in the price of crude oil.

As was discussed in the first section of the literature review, when the stock market index of a certain country is heavily composed of firms that are negatively impacted by oil price changes, it stands to reason that the stock market index will probably also be negatively impacted, and vice
versa in the case of market indices that are composed of firms that aren't so sensitive to oil price changes.

This is especially a problem not so much in the case of developed markets which are more diversified, but more so in the case of emerging stock markets who are more focused on certain industries. As Arouri (2011) stated, the overall relationship between the stock market index of a country and the oil prices is going to heavily depend on how the sectors of each country are composed.

### 2.3. Relationship between Stock Returns \& Different Types of Oil Price Shocks

One of the most important contributions to the literature is Killian's research (2008) on the different kinds of oil price shocks. While various papers had been written at that point, Killian criticized the literature, as most papers which investigated the relationship between oil price risk and stock returns incorporated oil price changes in the variables of their models, but assumed that the oil price risk could be treated as exogenous. In other words, they assumed a varying price for crude oil, while holding all the other variables constant. That said, it is widely accepted in the literature that the prices of crude oil rise during a period of global business cycle expansion. This means that there might be economic shocks that drive the stock returns upwards but also drive up the price of crude oil, making it very difficult to distinguish causal relationships between stock returns and oil prices.

Kilian showed that without knowing the underlying cause of the rise or drop of the oil prices, it's impossible to predict the implications of such changes accurately. More specifically, he distinguished three demand and supply shocks, namely: oil-supply shocks (shocks to the availability of crude oil in the physical market), aggregate demand shocks (shocks to the demand for crude oil which are created by fluctuations in the global business cycle, and precautionary demand shocks (shocks which arise due to changes in the precautionary demand for oil). The precautionary demand shocks have as a result a negative relationship to form between oil prices and stock returns
due to the uncertainty about possible supply shortfalls, while demand shocks due to the unanticipated economic expansion can lead to a positive relationship between oil prices and stock returns.

Kilian (2009) further expanded on his previous work regarding the decomposed oil price risk. Out of the three previously mentioned shocks, not all have been studied in detail in the literature. While oil supply shocks have been studied thoroughly (Hamilton, 2003; Kilian, 2008a), similar research hasn't been performed for the demand shocks. Although it had been acknowledged in the literature that demand shocks are an important factor, the quantification of these demand shocks had been a persistent problem. In this paper, Kilian constructed a monthly index of global real economic activity in order to measure the how the worldwide real economic activity drives the demand for commodities in the global markets.

More succinctly, in his models he used the percent change in global crude oil production as a proxy for oil supply shocks. He also used the index of real economic activity that he constructed as a proxy for aggregate demand shocks, and finally he used the real price of oil as a proxy for oil specific-demand shocks. Using a vector autoregressive model (VAR) approach, and with data in a monthly frequency, he showed that macroeconomic models that assume that oil prices are exogenous are possibly misleading and that the oil prices changes must be decomposed into the structural shocks that drive these changes.

This evidence was further reinforced by Kilian and Park (2009) who investigated the impact of oil price shocks on the S\&P 500 index, using monthly data for the time period 1973-2006. Using the structural VAR decomposition, Kilian and Park reached the conclusion that the U.S. real stock returns react differently to oil price shocks, depending on what was the underlying reason that drove the oil price to increase. More specifically, he concluded that shocks to the global aggregate demand, as well as shocks to the precautionary demand for oil that reflect fears over possible oil supply problems, are more important than shocks to the crude oil production in understanding changes in stock returns.

Following in Kilian's steps and employing his framework, Apergis and Miller (2008), delved into how the hidden structural shocks behind oil price changes affect the stock markets of eight developed countries (Australia, Canada, Germany, U.S., Japan, among others), using monthly data on
U.S. price per barrel of crude oil, the global real economic activity index developed by Kilian, crude oil production, as well as stock market returns of the various countries. While they used Kilian's framework, they also complemented it as in some of their models they used level variables from the oil market to replace the oil market shocks.

More specifically, they used global oil production, and not its percentage change, arguing that the percentage change in global oil production and the stock returns in Kilian's framework are stationary variables ( $\mathrm{I}(0)$ time-series), while the global real economic index that Kilian developed and the real price of crude oil are non-stationary variables (I(1) time-series). Thus, the VAR model estimated by Kilian is inconsistent. By using the global oil production, the real price of oil, and Kilian's index, all of the decomposed oil series are now $I(1)$, and they are consistent in a timeseries sense.

Güntner (2014), who examined the impact of crude oil demand and crude oil supply shocks on a set of 6 OECD countries, criticized the econometric model that Apergis and Miller (2009) employed for two reasons. According to Güntner, the Real Economic Activity index that Kilian developed should be in levels, since it's a business cycle index, and not in first differences as the authors employed. Also, since monthly data are employed, the lag length should be greater than seven to capture the impact of oil price shocks on the financial markets.

Of course, while many researchers subscribe to the idea that it's not possible to discern the true relationship between oil prices and the financial markets if the origins of oil price shocks aren't separated, there is also a growing literature around the fact that oil-supply shocks don't have any effect on the returns of stocks. Research such as the one performed by Abhyankar et al. (2013), or Apergis and Miller (2009), and Basher et al. (2012) among others, suggest that oil-supply price shocks don't haven't any effect on the financial markets. Bastianin et al. (2016) also studied how oil price shocks impact the stock market of G7 countries. Using a structural Vector Autoregressive (VAR) model for each of the seven countries and employing monthly data for the period 19732015, they also concluded that shocks to the supply of crude oil didn't impact any of the G7 countries.

Although it's been acknowledged in the literature that it's important to disentangle oil-demand shocks and oil-supply shocks, there have also been new proposed methods to achieve this. More specifically, in a relatively recent study Rapaport (2013) proposed that it's possible to disentangle demand and supply shocks by using the sign of the correlation between the stock returns and crude oil price changes. This is a methodology that was employed also by Cunado and Garcia (2014) who examined the impact of oil shocks on a set of European stock markets, using a Vector Autoregressive Model (VAR) and Vector Error Correction Models (VECM) and monthly frequency data. These researchers employed monthly data for the time period 1973-2011 for the following variables: industrial production, stock returns, short-term interest rates, as well as oil demand and supply shocks. The results were in line with the literature that the impacts of oil price changes were different depending on the underlying cause of the price change.

### 2.4. Relationship Between Stock Returns \& Oil Price Shocks in Net Oil Importing Countries vs Net Oil Exporting Countries

While many authors claim a negative relationship between stock returns and oil shocks, it stands to reason that as oil and gas firms aren't influenced the same as oil-consuming firms, that also the countries that are net-oil exporters aren't going to be impacted the same by positive oil price changes as the countries which are net-oil importers. One might expect that the stock returns of an oil-exporting country will even increase after a positive oil increase change. On the other hand, one would expect that oil price increases would have a negative effect on stock returns of net oilimporting countries.

Mohanty et al. (2011), using a multi-factor model with weekly data from 2005 to 2009, showed that whether the stock market of a country reacts positively or negatively to changes to the price of crude oil depends also on whether the country is a net producer of net consumer of oil resources. As was shown also by Bjornland (2009), who analysed the effects of increases in the price of crude
oil on Norwegian stock returns (oil-exporting country), and Arouri and Rault (2012), who examined the effects between stock markets situated in Gulf Cooperation Council (GCC) using a bootstrap panel Cointegration technique, there is actually a positive relationship between rising prices of oil and stock returns when the country is an oil-exporting country.

Salisu and Isah (2017) also found signs of asymmetries. In their study of eight net-oil importing countries and eight net-oil exporting countries using a nonlinear Panel ARDL model, they found oil-importing countries exhibit a negative relationship to oil price changes both in the short and the long run. In net-oil exporting countries, meanwhile, the study showed a positive relationship to oil price changes also both in the short and the long run.

There have also been studies which used Kilian's framework, to study the effect of the different types of oil shocks across net oil-importing and net oil-exporting countries. Wang et al. (2013) showed that a positive oil supply shock actually raises stock returns in oil-importing countries, which actually agrees with the theory as an increase in the production of crude oil will result in lower prices of crude oil. In the oil-exporting countries, on the other hand, the stock market returns experience a rise following by a decrease.

### 2.5 Time-Varying Relationship between Stock Returns \& Oil Price Shocks

Growing is also the literature that examines the links between financial markets and oil prices, but in a time-varying environment, as stock returns don't always respond the same in periods of economic recessions or economic expansions.

Choi and Hammoudeh (2010) estimated a DCC model to study the relationship between commodities such as WTI oil, copper, gold and silver to the S\&P 500 index for the time period 1990-2006, reaching the result that the correlations aren't constant, and have actually weakened in recent years, making these commodities useful for risk hedging purposes. Chang et al. (2013), studying the correlation between U.S. stock returns and crude oil prices, also reached a similar result. Mohaddes and Pesaran (2017) used a Global Vector Autoregressive Model (SVAR) and quarterly data,
to study the links between price of crude oil and stock returns for 27 countries. For the U.S. they ascertained that there was no constant relationship between the studied variables for the period of 1946-2017.

Building on Kilian's framework of considering the underlying cause of the oil price change, Filis et al. (2011), also researched the time-varying relationship between stock returns and oil prices, using Engle's (2002) DCC-GARCH model, but also expanded further by separating the oil exporting from the oil importing countries. The result of the paper was that non-economic crises such as wars and terrorist attacks create a more negative relationship between oil prices and stock returns, while economic crises or even economic expansions trigger a more positive relationship stock returns and crude oil prices.

Further research was also done by Broadstock and Filis (2014), who aimed to examine the timevarying correlations using Kilian's framework (different types of oil price shocks) using a ScalarBEKK model for data in the Unites States and China. They also expanded upon the existing literature by considering correlations with different sectors such as oil and gas, and banking.

Martin-Baraggan et al. (2015), using Gallegati's framework (Gallegati, 2012) that employs wavelets, showed that there is a stable relationship between oil prices and stock returns in non-shock periods, but this changes drastically in the presence of oil and financial shocks.

Finally, although not much research has been performed on this subject, there have also been papers which studied the different way that oil price changes affect stock returns depending on the quantiles of the stock returns. Studies such that of Peng et al. (2017) found asymmetric effects on stock returns in the lower and larger quantiles when there were large positive or negative changes in the price of oil.

## 3. Data

### 3.1. Data Set

This paper uses monthly time series spanning from July 1997 to December 2018 for a total of 258 observations on the following variables: (i) monthly closing prices of developed and emerging stock markets (in various currencies) for a total of 22 Stock Markets; (ii) the monthly future prices for Western Texas Intermediate Oil (in U.S. Dollars per barrel of Oil) which are traded on NYMEX; (iii) monthly Global Oil Production ( in Thousands barrels of oil per day); (iv) monthly Global Real Economic Activity which is an Index developed by Killian; (v) the monthly 3-Month Treasury Bill ( in percentages; seasonally adjusted); (vi) monthly closing prices of the S\&P 500 as a proxy for the Morgan Stanley Capital International (MSCI) World Index (in U.S. Dollars); (vii) and finally monthly frequency of the Trade Weighted U.S. Dollar Index: Major Currencies (seasonally adjusted).

As was mentioned previously, the data is consisted to a large degree of monthly closing stock prices for various stock markets across the globe. The data for the various stock markets were acquired from the Database of Yahoo Finance as there was no access available to the Bloomberg or Reuter's database. Both developed and emerging stock markets were included in this study.

More specifically, the Developed Stock Markets dataset consisted of stock markets of the following countries: Netherlands (NLD), Austria (AUT), Belgium (BEL), Germany (DEU), France (FRA), United Kingdom (GBR), Spain (ESP), Ireland (IRL), Japan (JPN), Sweden (SWE), and Switzerland (CHE).

Meanwhile, the Emerging Stock Markets dataset consisted of stock markets of the following countries: Hungary (HUN), Brazil (BRA), Indonesia (IDN), Korea (KOR), Pakistan (PAK), Argentina (ARG), Philippines (PHL), Peru (PER), China (CHN), Taiwan (TWN), and Turkey (TUR).

These various countries were selected for one main reason; mainly due to the fact that they have been trading for a relatively long period of time, so we have high number of observations despite using monthly frequency data. This fact, combined with the fact that Panel Methodology was employed, resulted in a very high number of total observations. Also, as part of this study is the examination of the existence of possible asymmetries between Emerging and Developed stock markets, it was thought prudent to include the same number of stock markets in each of the two categories.

The Stock Prices were also not transformed to the same currency (e.g. U.S. dollars) using Exchange Rates, as the results from our models would be biased since we would be including lots of different Exchange Rates. Instead, since we will be using the stock returns of each country without converting the data to the same currency.

The monthly WTI futures prices (NYMEX) were obtained from the U.S. Energy Information Administration Database (EIA), and they are the nearest to expire contract. The reason that futures prices were used and not spot prices is due to the fact that NYMEX oil futures are one of the most heavily traded oil contracts in the world. Also from the same database (EIA) was obtained the monthly time series for the Global Oil Production.

Another variable that was included in the model was a global index of dry cargo single voyage freight rates which was developed by Kilian, and is a proxy of Global Real Economic Activity. As Kilian (2009) argued, this global index that used freight rates is a valid proxy for Economic Activity, as the single voyage freight rates increase and decrease with rises and falls in Global Economic Activity. This Index was acquired from Kilian's personal website.

In an international Multi-Factor Model, it's vital to include an Exchange Rate Risk to examine how the stock market returns are affected by Exchange Rates. While the Exchange Rate Risk can be examined at a country level separately, it can also be approximated by using the Trade Weighted Exchange Index (TWEX), which is a weighted average of the U.S. dollar against a subset of other index currencies (e.g. the Euro area, Switzerland, Canada, China, Mexico, Malaysia, Indonesia, Argentina and others). This variable was obtained by the Database of the Federal Reserve Board of St. Louis.

Finally, another variable that is employed in the International Multi-Factor models is the Morgan Stanley Capital International (MSCI) World Index, which is a free-float adjusted market capitalization index that is used to measure the performance of the Global Market Equity. Although we were unable to acquire the MSCI World Index for the entire date range as the rest of our data, we were able to graph the returns of the MSCI World Index together with the returns of S\&P 500 for the time period between 2004 and 2018. As is also obvious on the Figure 1.1 below, the two timeseries are very highly correlated and they are moving together, which is why it was decided that the S\&P 500 index would be a good proxy for the MSCI World Index.


Figure 1.1. A Time-Series Plot: Returns of MSCI World Index and S\&P 500
Source: Yahoo Finance Database

### 3.2. Data Descriptive Statistics

The descriptive statistics of our data was broken down into three tables, Table 1.1. represents the summary descriptive statistics of the monthly stock returns of the developed stock markets, while Table 1.2. contains the summary descriptive statistics of the monthly stock returns of the emerging stock markets. Finally, Table 1.3. shows the summary descriptive statistics for the rest of the variables that were used in our models (mainly WTI returns, World Market Index etc.).

What is obvious at first glance is that for both the emerging stock markets and the developed ones, the standard deviation for these countries is relatively bigger than the average monthly stock returns. For the developed stock markets, two out of eleven stock markets have a negative average monthly return, while for the emerging stock markets, only one stock market has a negative average value.

In the developed stock markets (Table 1.1.), Germany and Austria have the highest average monthly return at $0.0034 \%$ and $0.0024 \%$ respectively, while Netherlands has the smallest average monthly return at $0.00034 \%$. Meanwhile, in the emerging stock markets (Table 1.2.), the highest average monthly returns are those of Turkey at $0.01495 \%$ and that of Argentina at $0.01390 \%$, while Taiwan has the lowest average monthly return at $-0,0013 \%$.

As far as volatility is concerned, in the developed stock markets (Table 1.1.), the highest value of standard deviation is observed for Sweden at $0.10311 \%$ and for Germany at $0.06255 \%$, while in the emerging stock markets (Table 1.2.), the countries with the highest values of standard deviation are Turkey at $0.11617 \%$ and Argentina at $0.10780 \%$.

Taking one look at the first two tables, what makes itself apparent is that with the exception of the stock market of Sweden, the emerging stock markets are more risky, with higher standard deviations than all those of all the developed stock markets.

The lowest standard deviation of our dataset is that of the United Kingdom at $0.040063 \%$, followed by the world market returns which have standard deviation of $0.043494 \%$, showing that English Stock market has a very well diversified portfolio.

While the oil market is considered one of the most volatile markets globally, we can see in Table 1.3. that the oil market with a standard deviation of $0.08677 \%$ is actually less volatile than the market of Turkey and Argentina, although it is still the third most volatile market of our dataset.

Table 1.1.
Summary Descriptive Statistics for Monthly Developed Stock Market Returns

| Netherlands A |  | Austria B | Belgium G | Germany | France | UK <br> GBR | $\begin{array}{cc} \text { Spain } & \mathrm{Ir} \\ \hline \text { ESP } \end{array}$ | $\frac{\text { Ireland } \quad \mathrm{J}}{\text { IRL }}$ | $\begin{array}{cc} \text { Japan } & \text { S } \\ \hline \text { JPN } \end{array}$ | $\begin{gathered} \text { Sweden } \\ \hline \text { SWE } \end{gathered}$ | Switzerland <br> CHE |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | NDL | AUT | BEL | DEU | FRA |  |  |  |  |  |  |
| Mean | 0.00034 | $4 \quad 0.00240$ | 0.00089 | 0.00340 | 0.00167 | 0.001228 | $8 \quad 0.00088$ | $8 \quad 0.00154$ | -6.11E-0 | - -0.00237 | $7 \quad 0.00138$ |
| Median | 0.00898 | $8 \quad 0.01000$ | 0.00934 | 40.00957 | 0.00931 | 0.00534 | 0.00699 | 90.00843 | 30.00650 | $0 \quad 0.00575$ | $5 \quad 0.00884$ |
| Maximum | 0.14568 | 80.13546 | 0.13514 | 40.19373 | 0.12588 | 0.084868 | $8 \quad 0.15378$ | $8 \quad 0.17825$ | $5 \quad 0.12088$ | 80.16078 | $8 \quad 0.12855$ |
| Minimum | -0.2262 | -0.3259 | -0.2408 | -0.2933 | -0.1922 | -0.13953 | -0.23878 | $8-0.23582$ | -0.27216 | 6-1.37355 | $5-0.20991$ |
| Std. Dev. | 0.05688 | 8 0.06108 | 0.04931 | 10.06255 | 0.05355 | 0.040063 | 330.06084 | $4 \quad 0.05704$ | 40.05693 | 30.10311 | 10.04420 |
| Skewness | -1.0114 | -1.2956 | -1.2583 | -0.8669 | -0.5744 | -0.624487 | $7-0.4307$ | -0.8985 | -0.7225 | $5-9.2321$ | -0.9332 |
| Kurtosis | 5.39286 | 67.21319 | 6.39256 | 65.66603 | 3.69486 | 3.69613 | - 4.11476 | 65.00016 | 64.28835 | 5122.997 | 75.42669 |
| Jarq-Bera | 105.136 | $6 \quad 261.987$ | 191.075 | 5108.337 | 19.3050 | 21.89366 | $6 \quad 21.2552$ | 277.4213 | 340.1385 | 5157845. | 5. 100.364 |
| Probability | 0.0000 | 0.00000 | 0.00000 | 0.00000 | 0.00006 | 0.000018 | $8 \quad 0.00002$ | 20.00000 | $0 \quad 0.00000$ | 00.00000 | $0 \quad 0.0000$ |
| Sum | 0.08926 | $6 \quad 0.61769$ | 0.22917 | 70.87411 | 10.43053 | 0.315528 | $8 \quad 0.22622$ | 20.39625 | $5-0.0156$ | -0.6082 | 2.3570 |
| Sm Sq. Dev. | 0.82852 | 20.95519 | 0.62260 | 1.00159 | 0.73415 | 0.410883 | 30.94760 | 00.83296 | 60.82983 | 3.72209 | 90.50013 |
| Obs. | 257 | 257 | 257 | 257 | 257 | 257 | 257 | 257 | 257 | 257 | 257 |

Table 1.2.
Summary Descriptive Statistics for Monthly Emerging Stock Market Returns

|  | Hungary | Brazil | Indonesia | Korea | Pakistan | Argentina Philippines Peru | China | Taiwan | Turkey |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | HUN | BRA | IDN | KOR | PAK | ARG | PHL | PER | CHN | TWN | TUR |  |
| Mean | 0.00623 | 0.00747 | 0.00836 | 0.0040 | 0.01138 | 0.01390 | 0.00408 | 0.00873 | 0.00288 | -0.00013 | 0.01495 |  |
| Median | 0.01237 | 0.00901 | 0.01485 | 0.0064 | 0.01894 | 0.01477 | 0.01084 | 0.008265 | 0.005879 | 0.005968 | 0.013730 |  |
| Maximum | 0.18403 | 0.21546 | 0.25019 | 0.41061 | 0.24111 | 0.39665 | 0.33166 | 0.32541 | 0.27805 | 0.22420 | 0.58658 |  |
| Minimum | -0.44725 | -0.50343 | -0.37855 | -0.31810 | -0.44876 | -0.49619 | -0.29896 | -0.46645 | -0.28272 | -0.21500 | -0.49471 |  |
| Std. Dev. | 0.07515 | 0.08530 | 0.07846 | 0.07977 | 0.08486 | 0.10780 | 0.06801 | 0.08146 | 0.07746 | 0.06632 | 0.11617 |  |
| Skewness | -1.27942 | -1.15216 | -1.21279 | 0.19349 | -1.17126 | -0.44124 | -0.40002 | -0.50174 | -0.30525 | -0.20092 | 0.21236 |  |
| Kurtosis | 8.81845 | 7.99905 | 8.53073 | 6.68500 | 8.44958 | 6.26642 | 7.42293 | 8.64389 | 4.96385 | 4.16671 | 7.43685 |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |
| Jarq Bera | 432.646 | 324.467 | 390.559 | 147.015 | 376.773 | 122.593 | 216.337 | 351.879 | 45.2998 | 16.3016 | 212.733 |  |
| Probability | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00028 | 0.00000 |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |
| Sum | 1.6027 | 1.92099 | 2.15040 | 1.0334 | 2.9248 | 3.57338 | 1.04856 | 2.24359 | 0.74009 | -0.03420 | 3.84446 |  |
| Sm Sq Dev 1.4457 | 1.86285 | 1.57605 | 1.6293 | 1.8437 | 2.97495 | 1.18418 | 1.69902 | 1.53634 | 1.12617 | 3.45517 |  |  |
| Obs. |  |  |  |  |  |  |  |  |  |  |  |  |

Table 1.3.
Summary Descriptive Statistics for World Index, Oil Price Returns, Exchange Rate Return \& Oil Production

|  | World Index | Oil Prices |  | Exchange Rate |  |
| :--- | :---: | ---: | ---: | ---: | ---: |
|  | MSCI | WTI Futures | TWEX | Oil Production | Economic Index. |
| Mean | 0.003758 | 0.003528 | $-6.11 \mathrm{E}-05$ | 0.001003 | 5.304440 |
| Median | 0.009050 | 0.014509 | 0.001466 | 0.001179 | -9.733682 |
| Maximum | 0.102307 | 0.214880 | 0.064736 | 0.028868 | 187.8978 |
| Minimum | -0.185636 | -0.312119 | -0.048328 | -0.024254 | -163.4309 |
| Std. Dev. | 0.043494 | 0.086776 | 0.016659 | 0.008056 | 70.73956 |
| Skewness | -0.841538 | -0.698133 | -0.033083 | -0.026582 | 0.606542 |
| Kurtosis | 4.638362 | 4.143762 | 3.577650 | 3.804661 | 2.778664 |
|  |  |  |  |  |  |
| Jarque-Bera | 59.07762 | 34.88507 | 3.620028 | 6.963683 | 16.28271 |
| Probability | 0.00000 | 0.000000 | 0.163652 | 0.030751 | 0.000291 |
| Sum |  |  |  |  |  |
| Sum Sq. Dev. | 0.965794 | 0.906682 | -0.015694 | 0.257817 | 1363.241 |
| Observations | 0.484283 | 1.927709 | 0.071049 | 0.016614 | 1281046. |

As far as skewness is concerned, we can see that all of the developed stock market returns (Table 1.1.) have a negative skewness, while in the emerging stock market dataset we also have negative values of skewness with the exception of Korea ( 0.19349 ) and Turkey $(0.21236)$, which means that the distributions are negatively skewed. We also observe that the countries that exhibit the highest values of skewness also exhibit the highest values of kurtosis. Austria and Hungary with skewness values of -1.2956 and -1.27942 respectively, have high values of kurtosis at 7.21319 and 8.81845. A closer study for these two countries showed that most of their returns are positive.

In all of the three tables, the results of the Jarque-Bera test are displayed, in which the Null Hypothesis of normality is tested. For both developed and emerging stock market returns we had very high values of the test statistic, leading us to reject the null hypothesis of normal distribution.

### 3.3. Graphing the Variables

The developed and emerging stock market indices as well our other independent variables, were also graphed against time in order to look for patterns, trends and cycles. In Figure 1.2. we can see the developed stock market indices in levels. Most of the developed stock markets have similar trends, which is perhaps to be expected as most are countries that belong to the European Union. In all of the individual graphs, we can observe a steep drop in 2008 that coincided with the Global Financial Crisis. The decline is especially steep in the cases of Ireland which is one of the countries along with Greece that was severely impacted by the Financial Crisis. Looking at the graphs, we also expect all the time-series in levels to be non-stationary.

We also spot a very steep drop in the stock market of Sweden, which coincided with the country's decision not to join the common European currency at the time. With the exception of Sweden, we can observe that all the other countries, including Japan and Switzerland have similar trends.

Meanwhile, in Figure 1.3., we can see the individual graphs of the emerging stock markets set against time. At first glance two things are obvious. First, the emerging stock markets also have similar trends between themselves and we still see the expected dives of the stock markets in periods of financial crisis. If we were to compare the two figures though, it's apparent that the emerging stock markets don't move exactly the same as the developed stock markets, having a continual upward trend, contrary to the developed stock markets which have a much more moderate upward trend.

Out of all the emerging stock markets, it was the Chinese stock market that was most heavily impacted by the Financial Crisis of 2008.


Figure 1.2. Time Series Plot: Stock Market Indices of Developed Countries
Source: Database of Yahoo Finance


Figure 1.3. Time Series Plot: Stock Market Indices of Emerging Countries
Source: Database of Yahoo Finance

MSCI WORLD INDEX


TOTAL WEIGHTED EXCHANGE RATE



3-MONTH T-BILL




Figure 1.3. Time Series Plot: MSCI World Index, WTI Futures, Global Economic Activity, Global Oil Production, TWEX, \& 3-Month T-Bill
Source: EIA, Killian's Website, Federal Reserve of St. Louis, Yahoo Finance Database

In Figure 1.3., we can see the rest of the variables, also in levels. It was only in 2015 that the Central Bank started increasing the interest rates again. We can also observe that Global Oil Production continues to have a steep upward trend which is similar to the World Index trend.

### 3.4. Correlation Matrix of Variables

Although in the previous step we observed that many of the stock markets, both developed and emerging, have similar trends, in Table 1.4. and 1.5. we also have the correlation matrix of the data in order to observe the relationships both between the countries themselves, but also between the variables that we used as independent variables.

In the two tables, we can see that all of the stock markets are positively correlated with the MSCI World Index. As a rule the developed stock markets seem to be significantly more highly correlated with the World Index than the emerging markets. In fact, as far as the developed stock markets are concerned, the strongest correlation to the MSCI World Index is that of the United Kingdom with a correlation of $80.9 \%$, while the weakest correlation with the exception of Sweden is that of Japan at $61.75 \%$. Meanwhile, the highest correlation to the MSCI World Index out of emerging stock markets is that of Hungary at $61.41 \%$, while the lowest is that of Pakistan at $14.49 \%$.

All the stock markets have also positive correlation with the Oil Market Returns, although the correlations aren't as strong as those with the MSCI World Index. The strongest correlation is between the Oil Market and the stock market of Peru at $33.76 \%$. This is to be expected perhaps as Peru has one the largest crude oil reserves in South and Central America. Generally, it seems that there is a trend as the emerging stock markets seem to be more highly correlated with the oil returns than the developed stock markets.

All the stock markets are also negatively correlated with Global Oil Production, except Turkey which has a very weak positive correlation. Once again the emerging stock markets seem to have a stronger correlation with the Global Oil Production than the developed stock markets.

Although in the next section, the data will be tested for stationarity, already from the correlation matrix there is no indication of Multicollinearity between our dependent variables and our independent ones. It's also important to note at this point that even in the cases of strong correlation, that correlation doesn't imply causation.

Table 1.4 Correlation Matrix (Part One)

|  | NDL | AUT | BEL | DEU | FRA | GBR | ESP | IRL | MSCI | JPN | SWE | CHE | HUN | BRA | IDN |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| NDL | 1,0000 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| AUT | 0,7128 | 1,0000 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| BEL | 0,8459 | 0,7533 | 1,0000 |  |  |  |  |  |  |  |  |  |  |  |  |
| DEU | 0,8681 | 0,6455 | 0,7587 | 1,0000 |  |  |  |  |  |  |  |  |  |  |  |
| FRA | 0,9033 | 0,6801 | 0,8152 | 0,9117 | 1,0000 |  |  |  |  |  |  |  |  |  |  |
| GBR | 0,8280 | 0,6973 | 0,7593 | 0,7860 | 0,8257 | 1,0000 |  |  |  |  |  |  |  |  |  |
| ESP | 0,7631 | 0,6376 | 0,7149 | 0,7761 | 0,8300 | 0,7342 | 1,0000 |  |  |  |  |  |  |  |  |
| IRL | 0,7106 | 0,6403 | 0,6962 | 0,6645 | 0,6785 | 0,6683 | 0,6070 | 1,0000 |  |  |  |  |  |  |  |
| MSC | 0,7630 | 0,6571 | 0,7192 | 0,7895 | 0,7813 | 0,8090 | 0,6975 | 0,6830 | 1,0000 |  |  |  |  |  |  |
| JPN | 0,5800 | 0,5857 | 0,4960 | 0,5839 | 0,5870 | 0,5430 | 0,5423 | 0,5241 | 0,6175 | 1,0000 |  |  |  |  |  |
| SWE | 0,4474 | 0,2892 | 0,3312 | 0,4430 | 0,4646 | 0,4034 | 0,4241 | 0,3280 | 0,3936 | 0,3764 | 1,0000 |  |  |  |  |
| CHE | 0,7881 | 0,6325 | 0,7485 | 0,7491 | 0,7911 | 0,7347 | 0,6905 | 0,6221 | 0,7182 | 0,5347 | 0,4046 | 1,0000 |  |  |  |
| HUN | 0,5742 | 0,6028 | 0,5208 | 0,5902 | 0,5929 | 0,5703 | 0,5977 | 0,4849 | 0,6084 | 0,4621 | 0,3159 | 0,5561 | $1,0000$ |  |  |
| BRA | 0,5428 | 0,5648 | 0,4792 | 0,5756 | 0,5667 | 0,5890 | 0,5981 | 0,4164 | 0,6191 | 0,4664 | 0,3309 | 0,5066 | 0,6057 | 1,0000 |  |
| IDN | 0,4827 | 0,5270 | 0,5016 | 0,4554 | 0,4375 | 0,4670 | 0,4172 | 0,3605 | 0,4731 | 0,4697 | 0,3536 | 0,4696 | 0,5261 | 0,4937 | 1,0000 |
| KOR | 0,5065 | 0,4484 | 0,4208 | 0,4822 | 0,4706 | 0,5279 | 0,4745 | 0,3924 | 0,5222 | 0,5186 | 0,3605 | 0,4031 | 0,4538 | 0,4477 | 0,5202 |
| PAK | 0,1506 | 0,1698 | 0,0546 | 0,1460 | 0,1302 | 0,1305 | 0,1202 | 0,2056 | 0,1449 | 0,1720 | 0,0807 | 0,0689 | 0,2775 | 0,2485 | 0,1181 |
| ARG | 0,3988 | 0,4890 | 0,3588 | 0,4127 | 0,3952 | 0,3964 | 0,4549 | 0,2828 | 0,4493 | 0,3818 | 0,2221 | 0,3298 | 0,4935 | 0,5315 | 0,4118 |
| PHL | 0,4200 | 0,4879 | 0,4316 | 0,4110 | 0,3750 | 0,4559 | 0,4058 | 0,3237 | 0,5157 | 0,3772 | 0,2449 | 0,4725 | 0,4549 | 0,4596 | 0,6320 |
| PER | 0,3946 | 0,5398 | 0,3786 | 0,3559 | 0,3332 | 0,3986 | 0,3526 | 0,3359 | 0,4383 | 0,3916 | 0,1480 | 0,2898 | 0,4739 | 0,5638 | 0,4762 |
| CHN | 0,2119 | 0,3063 | 0,2115 | 0,2555 | 0,2093 | 0,1926 | 0,2110 | 0,1693 | 0,2862 | 0,3061 | 0,0885 | 0,1692 | 0,2488 | 0,2828 | 0,2020 |
| TWN | 0,4965 | 0,4958 | 0,4184 | 0,5137 | 0,4694 | 0,4734 | 0,4671 | 0,4180 | 0,5321 | 0,4716 | 0,3518 | 0,3466 | 0,4103 | 0,5101 | 0,3665 |
| TUR | 0,4623 | 0,3983 | 0,3682 | 0,5125 | 0,4880 | 0,4936 | 0,4756 | 0,3574 | 0,4646 | 0,3687 | 0,1948 | 0,3907 | 0,4939 | 0,4776 | 0,3158 |
| WTI | 0,0784 | 0,2537 | 0,0403 | 0,0483 | 0,0616 | 0,0794 | 0,0575 | 0,1016 | 0,1585 | 0,2044 | -0,0104 | 0,0447 | 0,1841 | 0,1966 | 0,1048 |
| TWE | -0,0268 | -0,2191 | -0,1489 | -0,0492 | -0,0454 | -0,0920 | -0,1625 | -0,0381 | -0,2533 | -0,0898 | -0,0311 | -0,0203 | -0,167 | -0,2553 | -0,2753 |
| PRO | -0,0357 | -0,0665 | -0,1324 | -0,0449 | -0,0292 | 0,0050 | 0,0040 | 0,0082 | 0,0100 | 0,0221 | 0,0556 | 0,0078 | 0,0099 | -0,0224 | -0,1069 |
| ECO | -0,0045 | 0,0560 | -0,0027 | 0,0524 | 0,0033 | 0,0059 | 0,0422 | -0,0886 | -0,0089 | -0,0337 | 0,0443 | 0,0466 | 0,0068 | 0,0577 | 0,0904 |

Table 1.5. Correlation Matrix (Part Two)


### 3.5. Testing for Stationarity and Unit-Roots \& Transformation of Variables

Since we have time-series data, it's also important to formally test for stationarity, that is whether the statistical properties of our data, such as the mean, the variance etc., remain constant over time (Damodar Gujarati, 2012). We performed the Augmented Dickey and Fuller test (1979), and the Phillips-Perron test (1988).

More specifically, in both of these tests, we have the following Hypotheses:

Null Hypothesis $H_{0}$ : Existence of a Unit Root (Time-Series is non-stationary)

Alternative Hypothesis $H_{1}$ : There is no Unit Root (Time-Series is stationary)

Table 1.6. ADF Tests \& Phillips Perron Unit-Root Tests

| Level |  |  | 1st Differences |  | Order of Integration |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Variable | ADF Stat. | P-Value | Variable | ADF Stat. | P -Value |  |
| NDL | -1,751132 | 0,4043 | Dlog(NDL) | -15,39506 | 0,0000 | I(1) |
| AUT | -1,727557 | 0,4166 | Dlog(AUT) | -12,61157 | 0,0000 | I(1) |
| BEL | -2,090342 | 0,2489 | Dlog(BEL) | -13,6303 | 0,0000 | I(1) |
| DEU | -0,946733 | 0,7721 | Dlog(DEU) | -14,64052 | 0,0000 | I(1) |
| FRA | -2,173891 | 0,2165 | D $\log$ (FRA) | -14,66828 | 0,0000 | $\mathrm{I}(1)$ |
| GBR | -1,861543 | 0,3502 | Dlog(GBR) | -16,49329 | 0,0000 | I(1) |
| ESP | -2,488314 | 0,1195 | Dlog(ESP) | -14,91862 | 0,0000 | I(1) |
| IRL | -1,819561 | 0,3705 | Dlog(IRL) | -12,70851 | 0,0000 | I(1) |
| MSCI | -0,057156 | 0,9514 | Dlog(MSC) | -15,03001 | 0,0000 | I(1) |
| JPN | -1,603003 | 0,4796 | Dlog(JPN) | -14,95059 | 0,0000 | $\mathrm{I}(1)$ |
| SWE | -4,737336 | 0,0008 | Dlog(SWE) | -17,31594 | 0,0000 | $\mathrm{I}(0)$ |
| CHE | -1,836493 | 0,3628 | Dlog(CHE) | -14,10642 | 0,0000 | I(1) |
| HUN | 0,017467 | 0,9584 | Dlog(HUN) | -14,94958 | 0,0000 | I(1) |
| BRA | -0,371665 | 0,9105 | Dlog(BRA) | -14,01699 | 0,0000 | I(1) |
| IDN | 0,587838 | 0,9892 | Dlog(IDN) | -13,81299 | 0,0000 | I(1) |
| KOR | -1,075815 | 0,7258 | Dlog(KOR) | -15,47034 | 0,0000 | I(1) |
| PAK | 0,114386 | 0,9663 | Dlog(PAK) | -15,36875 | 0,0000 | I(1) |
| ARG | 3,918325 | 1,0000 | Dlog(ARG) | -8,090473 | 0,0000 | I(1) |
| PHL | 0,086654 | 0,9642 | Dlog(PHL) | -14,49975 | 0,0000 | I(1) |


| PER | $-1,432562$ | $-0,5661$ | Dlog(PER) | $-8,285406$ | 0,0000 | $\mathrm{I}(1)$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| CHN | $-2,715684$ | 0,0727 | $\operatorname{Dlog}(\mathrm{CHN})$ | $-9,040745$ | 0,0000 | $\mathrm{I}(1)$ |
| TWN | $-2,213496$ | 0,2021 | Dlog(TWN) | $-9,786564$ | 0,0000 | $\mathrm{I}(1)$ |
| TUR | $-0,851359$ | 0,8022 | Dlog(TUR) | $-16,58764$ | 0,0000 | $\mathrm{I}(1)$ |
| WTI | $-2,323256$ | 0,1654 | Dlog(WTI) | $-10,56599$ | 0,0000 | $\mathrm{I}(1)$ |
| TWEX | $-1,538886$ | 0,5124 | Dlog(TWE) | $-11,41759$ | 0,0000 | $\mathrm{I}(1)$ |
| PROD | $-0,583872$ | 0,8705 | Dlog(PRO) | $-13,42886$ | 0,0000 | $\mathrm{I}(1)$ |
| ECON | $-2,905422$ | 0,0461 | ECON | - | - | $\mathrm{I}(\mathrm{O})$ |

## PP Tests

| Level |  |  | 1st Differences |  | Order of Integration |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Variable | PP Stat. | P-Value | Variable | PP Stat. | P -Value |  |
| NDL | -1,948247 | 0,3099 | Dlog(NDL) | -15,43022 | 0,0000 | $\mathrm{I}(1)$ |
| AUT | -1,737751 | 0,4110 | Dlog(AUT) | -12,87909 | 0,0000 | I(1) |
| BEL | -2,197396 | 0,2078 | Dlog(BEL) | -13,90844 | 0,0000 | I(1) |
| DEU | -1,027213 | 0,7740 | Dlog(DEU) | -14,61358 | 0,0000 | I(1) |
| FRA | -2,528322 | 0,1099 | Dlog(FRA) | -14,80575 | 0,0000 | I(1) |
| GBR | -1,930738 | 0,3178 | Dlog(GBR) | -16,48674 | 0,0000 | I(1) |
| ESP | -2,649925 | 0,0844 | Dlog(ESP) | -14,91168 | 0,0000 | I(1) |
| IRL | -1,928882 | 0,3187 | D $\log$ (IRL) | -12,94907 | 0,0000 | I(1) |
| MSCI | -0,103849 | 0,9456 | Dlog(MSCI) | -15,02978 | 0,0000 | I(1) |
| JPN | -1,825547 | 0,3676 | Dlog(JPN) | $15,008844$ | 0,0000 | I(1) |
| SWE | -4,709311 | 0,0008 | Dlog(SWE) | -17,3696 | 0,0000 | I(0) |
| CHE | -1,985804 | 0,2931 | Dlog(CHE) | -14,10642 | 0,0000 | $\mathrm{I}(1)$ |
| HUN | -0,149007 | 0,9414 | Dlog(HUN) | -14,97352 | 0,0000 | I(1) |
| BRA | -0,51073 | 0,8856 | Dlog(BRA) | -13,97582 | 0,0000 | I(1) |
| IDN | 0,43246 | 0,9840 | Dlog(IDN) | -13,81643 | 0,0000 | I(1) |
| KOR | -1,135312 | 0,7022 | Dlog(KOR) | -15,48979 | 0,0000 | I(1) |
| PAK | -0,040297 | 0,9531 | Dlog(PAK) | -15,5578 | 0,0000 | I(1) |
| ARG | 2,414321 | 1,0000 | Dlog(ARG) | -17,24318 | 0,0000 | I(1) |
| PHL | -0,045937 | 0,9524 | Dlog(PHL) | -14,50505 | 0,0000 | I(1) |
| PER | -1,284591 | 0,6373 | Dlog(PER) | -14,71674 | 0,0000 | I(1) |
| CHN | -2,66915 | 0,0813 | Dlog(CHN) | -15,20455 | 0,0000 | I(1) |
| TWN | -2,440441 | 0,1317 | Dlog(TWN) | -15,2064 | 0,0000 | I(1) |
| TUR | -0,832707 | 0,8077 | Dlog(TUR) | -16,58368 | 0,0000 | I(1) |
| WTI | -2,153648 | 0,2241 | Dlog(WTI) | -10,50742 | 0,0000 | I(1) |
| TWEX | -1,34986 | 0,6066 | Dlog(TWEX) | -11,39667 | 0,0000 | $\mathrm{I}(1)$ |


| PROD | $-0,504336$ | 0,8868 | Dlog(PROD) | $-16,1588$ | 0,0000 | $\mathrm{I}(1)$ |
| :--- | :--- | :--- | :---: | :---: | :---: | :---: |
| ECON | $-2,318237$ | 0,1670 | D(ECON) | $-11,48674$ | 0,0000 | $\mathrm{I}(1)$ |

By performing the two tests on all of the variables, it was ascertained that with the exception of the variable of Global Economic Activity and the stock market index of Sweden, all of our series are non-stationary as we failed to reject the Null Hypothesis of No Unit root at the $95 \%$ confidence level. In the case of Global Economic Activity, the two tests that we run didn't reach the same result, so we still took first differences.

In the case of the stock market index of Sweden, as was mentioned previously in the section where the variables were graphed, there was a very steep drop in the stock market index possibly due to the fact that Sweden chose not to join the European Union at the time. When we accounted for this structural break, the series turned out that it was indeed non-stationary as well, so we still took first differences.

As was shown in Table 1.6., all of our variables are Integrated of Order I as we had to take first differences to make them stationary. We also took log differences, so that we can reduce possible heteroscedasticity.

## 4. Methodology and Models

### 4.1. International Multi-Factor Models Theory

This study employs an international-multi factor model which is a methodology closely related with the renowned International Capital Asset Pricing Model (CAPM), with the addition that it also allows for both conditional and unconditional risk factors, a methodology used by Sadorsky (2006). While the CAPM (Black, 1972) focuses mainly on the market risk, a multi-factor model incorporates many different sources of risk inside the model, such as Oil factors, policy uncertainty and others.

Initially, many empirical papers used the methodology established by Fama and MacBeth (1973), in which the relationship between betas and returns is studied. This is basically a two-step process. In the first stage, multi-factor models are estimated using OLS in order to estimate the various betas. In the second stage, a panel methodology is employed in which the dependent variables are still the asset returns, but the independent variables this time are the betas that were calculated in the first step.

While these models were used extensively and had their uses, it was Campbell et al. (1997) who pointed some certain limitations. According to Campbell, this approach led to standard errors of the coefficient in the second step of the process to be too high due to the fact that it ignored completely the estimation errors in the first stage of the process.

This is the reason that in the current study, we will be using the alternative methodology proposed by Pettengill et al. (1995). According to Pettengill et al. it's important to differentiate between expected returns, as they are analysed in the literature, and realized returns, as are observed in reality.

What Pettengill argued was that when estimating the various models, we are using actual returns and not forecasted values, which has as a result for a conditional relationship to form between risk and return. This conditional relationship depends both on the sign but also at the size of market returns. According to the literature, if the market returns are positive, then we should observe a
positive relationship between our dependent variable and the beta, whereas if the market returns are negative, we should observe a negative relationship between our returns and the betas. This is why it's important to include dummy variables in the model to account for when we have an up or down market. This methodology is further applied in multi-factor models which include not just market risk but also oil risk and other variables. This is why it's important to account not just for when the world market is up or down, but also for when the oil market is up or down.

While Sadorsky included WTI futures as a proxy for Oil Market risk in his international multifactor model, in this study we will estimate a more expansive model by including certain other variables related to the Oil Market, which is also one of the contributions of this study. As was mentioned previously in the Literature Review section, Kilian (2009) argued that there are certain factors that affect both the stock returns and the oil market returns, and that it's wrong to assume that oil is exogenous.

Essentially, according to Kilian, stocks might react differently to an oil price shock depending on the cause of this shock. If oil prices were go up for example due to an economic expansion which creates a need for more oil, then it's possible that stock returns will react positively to an increase in the price of oil, likewise if the oil prices increase due to oil shortages which are caused by lower oil production, then the stock returns will be negatively impacted.

Following in Kilian's example, two more extra variables will be included in our models, namely the percentage change of Global Oil Production, as well as the Global Real Economic Activity, which is an index that Kilian developed. Global Oil Production will be a proxy for oil-supply risk, Global Real Economic Activity will be a proxy for global-demand risk which will capture the demand for industrial commodities, and finally the Oil Prices will be a proxy for oil-market specific risk, which has to do with the increased global uncertainty about future oil supply.

Also, in the international multi-factor model it's important to make certain assumptions such as that we have purchasing power parity and integrated capital markets. In the case that these assumptions aren't valid then the investors will also face exchange rate risk. This is why it's important to include exchange rates as a variable in our model. Due to the high number of countries that are employed in this current study instead of using many different exchange rates, we approximate the
exchange rate risk by using the Trade Weighted Exchange Rate Index, which is a weighted average of the U.S. dollar against a subset of other major index currencies, a methodology proposed by Ferson and Harvey (1994).

Finally, in the case that stock returns aren't normally distributed, as in our case, the inclusion of Skewness and Kurtosis is justified since according to Harvey and Siddique (2000) and Bekaert et al. (1997), investors care about the Skewness and of their portfolio. Standard Deviation, as a measure of Total Risk, is also included in models of the Literature as investors who are willing to accept the additional risk of a stock with higher standard deviation should obtain a higher return. Sadorsky also employed higher moments in his framework, citing that skewness and kurtosis might be an additional source of risk.

### 4.2. Methodology

Using Sadorsky's framework, we followed a two-step process. Initially, the monthly excess stock returns for the developed and emerging stock markets were calculated by subtracting the monthly yield on a three month Treasury bill from the 22 compounded stock market returns. The monthly excess stock returns were also calculated by subtracting the monthly yield on the three month Treasury bill from the compounded returns of the MSCI World Index.

After all the various data transformations, the first step of our methodology is to estimate the world market betas, the oil betas, the exchange rate betas, as well as the global oil production betas and the global economic activity betas using the following multi factor model:

$$
R_{i t}=c+b_{m, i t} M R_{t}+b_{o, i t} \text { OIL }_{t}+b_{e x, i t} T W E X_{t}+b_{p, i t} \text { PROD }_{t}+b_{e c, i t} E C O N_{t}+e_{i t} \text { (1) }
$$

In the above Equation (1), $R_{i t}$ are the monthly excess stock returns (in which i denoted the country while t denoted the time period), $M R_{t}$ are the monthly excess returns on the MSCI World Index, $O I L_{t}$ are the monthly returns on oil prices, $T W E X_{t}$ are the monthly exchange rate returns, $P R O D_{t}$ is the monthly Global Oil Production in percentages, and $E C O N_{t}$ is the Global Economic Activity Index which is in levels according to Kilian's framework. Finally, $e_{i t}$ is the independently and identically distributed error term.

Eq. (1) is estimated for every country using OLS and a rolling fixed regression method for a window of 60 observations. According to Brealey \& Myers (2003) the recommended window length for financial models is five years' worth of data. So, if we were to include daily observations for example we would be using a rolling window of 1250 observations, whereas in our case we are using 60 observations. For each estimation period we calculate and store the market beta, the oil beta, and exchange rate beta, the oil production beta and the economic activity beta. After all the betas are stored, the estimation window is moved forward by adding one new observation and dropping the most distant observation, and then the new betas are calculated and stored. For every estimation period the window length is always fixed at 60 monthly observations. In this study, a total of 4356 regressions were run in order to estimate and store 21780 betas.

Also, since certain of our models will include risk metrics such as Total Risk, Skewness and Kurtosis, in every estimation window we also estimated and stored the standard deviation, the skewness and the Kurtosis for each of the countries' stock returns.

In the second step of our study, we employed Panel Methodology in order to test the unconditional as well as the conditional relationship between excess stock returns and the betas that we obtained from the first stage of our estimation.

More specifically first we estimated an unconditional equation:

$$
\begin{equation*}
R_{i, t}=\gamma_{0}+\gamma_{m 1} b_{m, i t}+\gamma_{o 1} b_{o, i t}+\gamma_{e x 1} b_{e x, i t}+\gamma_{p 1} b_{p, i t}+\gamma_{e c 1} b_{e c, i t}+e_{2 t} \tag{2}
\end{equation*}
$$

Where $b_{m, i t}, b_{o, i t}, b_{e x, i t}, b_{p, i t} \quad b_{e c, i t}$ are the market, oil, exchange rate, oil production and economic activity betas respectively that were estimated and recorded in the previous step.

In order to use the methodology of Pettengill et al. (1995), so that we can test for the conditional relationship between betas and returns, we created a series of dummy variables, and estimated the following equation using panel methodology:

$$
\begin{aligned}
R_{i, t}=\gamma_{0}+ & \gamma_{m 2} D_{1 t} b_{m, i t}+\gamma_{m 3}\left(1-D_{1 t}\right) b_{m, i t}+\gamma_{o 2} D_{2 t} b_{o, i t}+\gamma_{o 3}\left(1-D_{2 t}\right) b_{o, i t} \\
& +\quad \gamma_{e x 2} b_{e x, i t}+\gamma_{p 2} D_{3 t} b_{p, i t}+\gamma_{p 3}\left(1-D_{3 t}\right) b_{p, i t}+\gamma_{e c 2} D_{4 t} b_{e c, i t} \\
& +\gamma_{e c 3}\left(1-D_{4 t}\right) b_{e c, i t}+e_{3 t} \text { (3) }
\end{aligned}
$$

In Eq. 3, $D_{1 t}$ is a dummy variable that takes the value of 1 when the MSCI World market returns are positive and 0 when the returns are negative, $D_{2 t}$ is a dummy variable that takes the value of 1 when the oil market returns are positive and 0 when the returns are negative. Likewise $D_{3 t}$ and $D_{4 t}$ are dummy variables that take the value of 1 when there is a positive increase in the Global Oil Production and the Global Economic Activity Index likewise, and they take the value of 0 otherwise.

In all of the conditional equations, according to the literature we expect the $\gamma_{m 2}$ and $\gamma_{o 2}$ coefficients to be positive as we have an up world and oil market while we expect the $\gamma_{m 3}$ and $\gamma_{o 3}$ coefficients to be negative as we have a down market.

In Eq. 4, we have once more a conditional equation, only this time we are also including a risk metric, and more specifically total risk. As was mentioned previously, the proxy for total risk is the rolling standard deviation of the various markets, estimated over the same time periods as the rest of the betas. Total risk is a risk metric we use as it expresses the combination of systematic and unsystematic risk, that is market and the firm specific risk.

Similarly to the previous model, we included dummy variables to account for the up and down markets, with the dummies taking the same values as in the previous example. For the total risk
variable the World Market Dummy was used, which takes values of 1 when we have an up market, and 0 otherwise.

$$
\begin{align*}
& R_{i, t}=\gamma_{0}+\gamma_{m 2} D_{1 t} b_{m, i t}+\gamma_{m 3}\left(1-D_{1 t}\right) b_{m, i t}+\gamma_{o 2} D_{2 t} b_{o, i t}+\gamma_{o 3}\left(1-D_{2 t}\right) b_{o, i t} \\
&+\quad \gamma_{e x 2} b_{e x, i t}+\gamma_{p 2} D_{3 t} b_{p, i t}+\gamma_{p 3}\left(1-D_{3 t}\right) b_{p, i t}+\gamma_{e c 2} D_{4 t} b_{e c, i t} \\
&+\gamma_{e c 3}\left(1-D_{4 t}\right) b_{e c, i t}+\quad \gamma_{T 2} D_{1 t} T R_{i t}+\gamma_{T 3}\left(1-D_{1 t}\right) T R_{i t}+e_{5 t} \tag{4}
\end{align*}
$$

Following the previous equations, in Eq. 5 we estimated once again a conditional model, including this time skewness as a risk metric, while in Eq. 6 similarly we estimated a conditional model including kurtosis this time as an independent variable.

$$
\begin{align*}
& R_{i, t}=\gamma_{0}+\gamma_{m 2} D_{1 t} b_{m, i t}+\gamma_{m 3}\left(1-D_{1 t}\right) b_{m, i t}+\gamma_{o 2} D_{2 t} b_{o, i t}+\gamma_{o 3}\left(1-D_{2 t}\right) b_{o, i t} \\
&+\gamma_{e x 2} b_{e x, i t}+\gamma_{p 2} D_{3 t} b_{p, i t}+\gamma_{p 3}\left(1-D_{3 t}\right) b_{p, i t}+\gamma_{e c 2} D_{4 t} b_{e c, i t} \\
&+\gamma_{e c 3}\left(1-D_{4 t}\right) b_{e c, i t}+\gamma_{S 2} D_{1 t} S K E W_{i t}+\gamma_{S 3}\left(1-D_{1 t}\right) S K E W_{i t}+e_{7 t} \tag{5}
\end{align*}
$$

$$
\begin{align*}
R_{i, t}=\gamma_{0}+ & \gamma_{m 2} D_{1 t} b_{m, i t}+\gamma_{m 3}\left(1-D_{1 t}\right) b_{m, i t}+\gamma_{o 2} D_{2 t} b_{o, i t}+\gamma_{o 3}\left(1-D_{2 t}\right) b_{o, i t} \\
& +\gamma_{e x 2} b_{e x, i t}+\gamma_{p 2} D_{3 t} b_{p, i t}+\gamma_{p 3}\left(1-D_{3 t}\right) b_{p, i t}+\gamma_{e c 2} D_{4 t} b_{e c, i t} \\
& +\gamma_{e c 3}\left(1-D_{4 t}\right) b_{e c, i t}+\gamma_{T 2} D_{1 t} K U R T_{i t}+\gamma_{T 3}\left(1-D_{1 t}\right) K U R T+e_{9 t} \tag{6}
\end{align*}
$$

Finally, another contribution of this study is that we don't only use developed or emerging stock market data, but we are employing both in our estimations. In the previous models while we tested the relationship of the returns to the various betas, even taking into account the fact that we had an up-market (positive world returns) or a down-market (negative world returns), we didn't really
consider the fact that the emerging stock markets might be impacted differently from the developed stock markets.

As we observed both in the section where the descriptive statistics were presented and the section where the correlation matric was analysed, the emerging stock markets have generally higher standard deviations, and they are also more highly correlated with variables such as Oil and generally the two stock market categories don't always have similar trends. This is why in the following equations (Eq. 7-10), another interactive dummy was included. $D_{D E V}$ takes values of 1 when we're talking about a developed stock market and 0 when it's an emerging stock market.

More specifically $\gamma_{m 4}, \gamma_{o 4}, \gamma_{p 4}, \gamma_{e c 4}, \gamma_{T 4}, \gamma_{S 4}, \gamma_{K 4}$ are the coefficients for when we have developed stock markets and the market is up, $\gamma_{m 5}, \gamma_{o 5}, \gamma_{p 5}, \gamma_{e c 5}, \gamma_{T 5}, \gamma_{S 5}, \gamma_{K 5}$ are the coefficients for when we have an emerging stock market and the market is up. Likewise $\gamma_{m 6}, \gamma_{o 6}, \gamma_{p 6}, \gamma_{e c 6}, \gamma_{T 6}, \gamma_{S 6}, \gamma_{K 6}$ are the coefficients for when we have a developed stock market and the market is down, and finally $\gamma_{m 7}, \gamma_{o 7}, \gamma_{p 7}, \gamma_{e c 7}, \gamma_{T 7}, \gamma_{S 7}, \gamma_{K 7}$ are the coefficients of interest for when we have an emerging stock market and the market is down.

$$
\begin{aligned}
R_{i, t}=\gamma_{0}+ & \gamma_{m 4} D_{D E V} D_{1 t} b_{m, i t}+\gamma_{m 5}\left(1-D_{D E V}\right) D_{1 t} b_{m, i t}+\gamma_{m 6} D_{D E V}\left(1-D_{1 t}\right) b_{m, i t}+\gamma_{m 7}(1 \\
& \left.-D_{D E V}\right)\left(1-D_{1 t}\right) b_{m, i t}+\gamma_{o 4} D_{D E V} D_{2 t} b_{o, i t}+\gamma_{o 5}\left(1-D_{D E V}\right) D_{2 t} b_{o, i t} \\
& +\gamma_{o 6} D_{D E V}\left(1-D_{2 t}\right) b_{o, i t}+\gamma_{o 7}\left(1-D_{D E V}\right)\left(1-D_{2 t}\right) b_{o, i t}+\gamma_{e x 2} D_{D E V} b_{e x, i t} \\
& +\gamma_{e x 2}\left(1-D_{D E V}\right) b_{e x, i t}+\gamma_{p 4} D_{D E V} D_{3 t} b_{p, i t}+\gamma_{p 5}\left(1-D_{D E V}\right) D_{3 t} b_{p, i t} \\
& +\gamma_{p 6} D_{D E V}\left(1-D_{3 t}\right) b_{p, i t}+\gamma_{p 7}\left(1-D_{D E V}\right)\left(1-D_{3 t}\right) b_{p, i t}+\gamma_{e c 4} D_{D E V} D_{4 t} b_{e c, i t} \\
& +\gamma_{e c 5}\left(1-D_{D E V}\right) D_{4 t} b_{e c, i t}+\gamma_{e c 6} D_{D E V}\left(1-D_{4 t}\right) b_{e c, i t}+\gamma_{e c 7}(1 \\
& \left.-D_{D E V}\right)\left(1-D_{4 t}\right) b_{e c, i t}+e_{10 t}(7)
\end{aligned}
$$

$$
\begin{aligned}
R_{i, t}=\gamma_{0}+ & \gamma_{m 4} D_{D E V} D_{1 t} b_{m, i t}+\gamma_{m 5}\left(1-D_{D E V}\right) D_{1 t} b_{m, i t}+\gamma_{m 6} D_{D E V}\left(1-D_{1 t}\right) b_{m, i t} \\
& +\gamma_{m 7}\left(1-D_{D E V}\right)\left(1-D_{1 t}\right) b_{m, i t}+\gamma_{o 4} D_{D E V} D_{2 t} b_{o, i t}+\gamma_{o 5}\left(1-D_{D E V}\right) D_{2 t} b_{o, i t} \\
& +\gamma_{o 6} D_{D E V}\left(1-D_{2 t}\right) b_{o, i t}+\gamma_{o 7}\left(1-D_{D E V}\right)\left(1-D_{2 t}\right) b_{o, i t}+\gamma_{e x 2} D_{D E V} b_{e x, i t} \\
& +\gamma_{e x 2}\left(1-D_{D E V}\right) b_{e x, i t}+\gamma_{p 4} D_{D E V} D_{3 t} b_{p, i t}+\gamma_{p 5}\left(1-D_{D E V}\right) D_{3 t} b_{p, i t} \\
& +\gamma_{p 6} D_{D E V}\left(1-D_{3 t}\right) b_{p, i t}+\gamma_{p 7}\left(1-D_{D E V}\right)\left(1-D_{3 t}\right) b_{p, i t}+\gamma_{e c 4} D_{D E V} D_{4 t} b_{e c, i t} \\
& +\gamma_{e c 5}\left(1-D_{D E V}\right) D_{4 t} b_{e c, i t}+\gamma_{e c 6} D_{D E V}\left(1-D_{4 t}\right) b_{e c, i t} \\
& +\gamma_{e c 7}\left(1-D_{D E V}\right)\left(1-D_{4 t}\right) b_{e c, i t}+\gamma_{T 4} D_{D E V} D_{1 t} T R_{i t}+\gamma_{T 5}\left(1-D_{D E V}\right) D_{1 t} T R_{i t} \\
& +\gamma_{T 6} D_{D E V}\left(1-D_{1 t}\right) T R_{i t}+\gamma_{T 7}\left(1-D_{D E V}\right)\left(1-D_{1 t}\right) T R_{i t}+e_{11 t}
\end{aligned}
$$

$$
\begin{aligned}
R_{i, t}=\gamma_{0}+ & \gamma_{m 4} \\
& D_{D E V} D_{1 t} b_{m, i t}+\gamma_{m 5}\left(1-D_{D E V}\right) D_{1 t} b_{m, i t}+\gamma_{m 6} D_{D E V}\left(1-D_{1 t}\right) b_{m, i t} \\
& +\gamma_{m 7}\left(1-D_{D E V}\right)\left(1-D_{1 t}\right) b_{m, i t}+\gamma_{o 4} D_{D E V} D_{2 t} b_{o, i t}+\gamma_{o 5}\left(1-D_{D E V}\right) D_{2 t} b_{o, i t} \\
& +\gamma_{o 6} D_{D E V}\left(1-D_{2 t}\right) b_{o, i t}+\gamma_{o 7}\left(1-D_{D E V}\right)\left(1-D_{2 t}\right) b_{o, i t}+\gamma_{e x 2} D_{D E V} b_{e x, i t} \\
& +\gamma_{e x 2}\left(1-D_{D E V}\right) b_{e x, i t}+\gamma_{p 4} D_{D E V} D_{3 t} b_{p, i t}+\gamma_{p 5}\left(1-D_{D E V}\right) D_{3 t} b_{p, i t} \\
& +\gamma_{p 6} D_{D E V}\left(1-D_{3 t}\right) b_{p, i t}+\gamma_{p 7}\left(1-D_{D E V}\right)\left(1-D_{3 t}\right) b_{p, i t}+\gamma_{e c 4} D_{D E V} D_{4 t} b_{e c, i t} \\
& +\gamma_{e c 5}\left(1-D_{D E V}\right) D_{4 t} b_{e c, i t}+\gamma_{e c 6} D_{D E V}\left(1-D_{4 t}\right) b_{e c, i t} \\
& +\gamma_{e c 7}\left(1-D_{D E V}\right)\left(1-D_{4 t}\right) b_{e c, i t}+\gamma_{S 4} D_{D E V} D_{1 t} S K E W_{i t}+\gamma_{S 5}(1 \\
& \left.-D_{D E V}\right) D_{1 t} S K E W_{i t}+\gamma_{S 6} D_{D E V}\left(1-D_{1 t}\right) S K E W_{i t}+\gamma_{S 7}(1 \\
& \left.-D_{D E V}\right)\left(1-D_{1 t}\right) S K E W_{i t}+e_{12 t}(9)
\end{aligned}
$$

$$
\begin{aligned}
R_{i, t}=\gamma_{0}+ & \gamma_{m 4} D_{D E V} D_{1 t} b_{m, i t}+\gamma_{m 5}\left(1-D_{D E V}\right) D_{1 t} b_{m, i t}+\gamma_{m 6} D_{D E V}\left(1-D_{1 t}\right) b_{m, i t} \\
& +\gamma_{m 7}\left(1-D_{D E V}\right)\left(1-D_{1 t}\right) b_{m, i t}+\gamma_{o 4} D_{D E V} D_{2 t} b_{o, i t}+\gamma_{o 5}\left(1-D_{D E V}\right) D_{2 t} b_{o, i t} \\
& +\gamma_{o 6} D_{D E V}\left(1-D_{2 t}\right) b_{o, i t}+\gamma_{o 7}\left(1-D_{D E V}\right)\left(1-D_{2 t}\right) b_{o, i t}+\gamma_{e x 2} D_{D E V} b_{e x, i t} \\
& +\gamma_{e x 2}\left(1-D_{D E V}\right) b_{e x, i t}+\gamma_{p 4} D_{D E V} D_{3 t} b_{p, i t}+\gamma_{p 5}\left(1-D_{D E V}\right) D_{3 t} b_{p, i t} \\
& +\gamma_{p 6} D_{D E V}\left(1-D_{3 t}\right) b_{p, i t}+\gamma_{p 7}\left(1-D_{D E V}\right)\left(1-D_{3 t}\right) b_{p, i t}+\gamma_{e c 4} D_{D E V} D_{4 t} b_{e c, i t} \\
& +\gamma_{e c 5}\left(1-D_{D E V}\right) D_{4 t} b_{e c, i t}+\gamma_{e c 6} D_{D E V}\left(1-D_{4 t}\right) b_{e c, i t} \\
& +\gamma_{e c 7}\left(1-D_{D E V}\right)\left(1-D_{4 t}\right) b_{e c, i t}+\gamma_{K 4} D_{D E V} D_{1 t} K U R T_{i t}+\gamma_{K 5}(1 \\
& \left.-D_{D E V}\right) D_{1 t} K U R T_{i t}+\gamma_{K 6} D_{D E V}\left(1-D_{1 t}\right) K U R T_{i t}+\gamma_{K 7}(1 \\
& \left.-D_{D E V}\right)\left(1-D_{1 t}\right) K U R T_{i t}+e_{13 t}(10)
\end{aligned}
$$

Finally, as was previously mentioned, certain risk metrics such as kurtosis and skewness are strongly correlated, which is why we cannot have more than one risk metric as a regressor as Multicollinearity issues are certain to arise. This is why in all the previous models we used Skewness, Kurtosis and Total Risk on their own.

## 5. Empirical Results

In table 1.7 and 1.8 the results of our panel regressions are presented in which the relationship between the various risk metrics of our models and the excess stock returns is investigated. The first model investigates the relationship between the excess stock returns and the world market risk, the oil price risk, the exchange rate risk, the global demand risk which captures the demand for industrial commodities, and the oil supply risk.

The second model is a conditional model which investigates the relationship between excess stock returns and the aforementioned variables, only this time, it investigates the relationships taking into account when the markets are up or down.

Model 3 investigates the conditional relationships between excess stock returns and world market risk, oil price risk, exchange rate risk, global oil demand risk, oil-supply risk, and total risk while also taking into account when the markets are up or down.

Model 4 and 5 also investigate the conditional relationship between stock returns and the previously mentioned variables only instead of including total risk in the model, model 4 includes skewness as an independent variable, and model 5 includes kurtosis.

Model 6 investigates the conditional relationship between excess stock returns and world market risk, oil-market risk, exchange rate risk, global oil demand risk, and oil supply risk, only this time the model takes into account not only when the markets are up or down but also how differently developed and emerging stock markets are affected by these risks.

Model 7 through 9 investigate the same relationships as model 6, only Model 7 includes also total risk, Model 8 includes skewness as a risk metric, and Model 9 includes kurtosis.

As is observed in table 1.7 and table 1.8, almost all of the models have high values of the DurbinWatson statistic and it's very close to two, so there is no sign of first order serial correlation or spurious results, which is to be expected as all of our series are stationary as we saw in a previous
section. We also have very high significant values of the F-Statistic which are an indication that the coefficients we have included in our models are fitting our data well. It's worth noting also that the $t$-statistics in all of our models were estimated using heteroscedasticity period robust standard errors in order to control for the possible existence of heteroscedasticity as well as serial correlation.

In all of our models the intercept has a negative coefficient and is statistically significant at the 5\% level of significance, except for the constant in the first model which is insignificant and the intercept in the fourth model which is statistically significant but at the $10 \%$ level of significance. All of our models have also relatively high values of R squared close to $30 \%$, with only our first unconditional model having a really low value of $1,3 \%$, which is though similar to other unconditional international multi-factor models employed in the literature.

Another similar trend that is observed in all of our models is that the coefficient of exchange rate risk is insignificant both for the emerging and the developed stock markets, and it's only statistically significant at the $5 \%$ level of significance in the first unconditional model, which is similar to the results expected according to the literature.

In our first model, which is unconditional, the estimated coefficient of the world market risk is negative and significant, and the interpretation is that one unit increase in the world market risk will lead to a 0,0178 unit decrease in the excess stock market returns, which is obviously against our expectations since we expect the stock returns to go up when the risk goes up.

The oil-market specific risk which is captured by the Oil Price Beta is statistically insignificant, as is also the global oil demand risk and the oil-supply risk. This seems to change though as we turn towards our conditional models.

In all of our conditional models, the signs of the estimated coefficients of the market risk, the oil price risk, the oil-supply risk and the global demand risk are consistent with those of the literature. More precisely we can observe a pattern arising in models 2 through 5 as in all of our models when we have up markets we can observe a statistically significant positive relationship between stock returns and market betas at the $5 \%$ level of significance, while there is also a statistically significant negative relationship between stock returns and market betas when the markets are down. This
means that high beta markets experience higher premiums than those markets with lower betas. Similarly, our results imply that when the markets are down, the markets with the higher betas suffer greater losses than those which have a lower beta.

We can observe similar relationships for the oil markets, as we also have significant positive coefficients for the oil price risk when the oil markets are up at the $5 \%$ level of significance, as well as significant negative relationship when the markets are down. These results reaffirm the fact that oil betas are indeed significant and influence the stock market returns. It's worth noting that the stock returns aren't influenced to the same degree though when we have up or down markets.

As we can see in Model 3, when the oil markets are up, one unit increase in the oil betas leads to 0,061019 units increase in excess stock returns, but when the markets are down, one unit increase in the oil betas leads to a 0.07557 unit decrease in the excess stock returns.

As far as oil-supply risk is concerned, we can see that the signs of estimated coefficients in all of our estimated models are also according to the theory, as when there is an increase in global oil production we expect the stock markets to be positively impacted while we expected a decrease in oil-supply to negatively impact the stock returns. In models $3,5, \& 6$, the coefficients of the oilsupply risk are significant at $10 \%$ level of significance while in model 5 the coefficients are significant at the $5 \%$ level.

The coefficients for the oil global demand risk also have signs according to the theory, that is, they are positive when we have an up market and negative when we have a negative market. The coefficients for the oil-global demand risk are very significant at the $5 \%$ level of significance but only when the markets are up, and insignificant otherwise.

In Model 3, the conditional relationship between the excess stock returns and total risk is investigated. As we can see in table 1.7 the coefficients for the up market is positive and significant at the $10 \%$ level of significance, while for the down market the sign of the coefficient is contrary to the literature and it's also insignificant, which means that total risk doesn't play a very important role.

Similarly, in Model 4, we observe the relationship for the stock returns and skewness. The estimated coefficients are very significant at the $5 \%$ level of significance, although we observe a negative relationship to the returns when the market is up, and a positive relationship when the market is down. These results imply that skewness does play a significant role in stock returns.

In Model 5, we study the relationship between kurtosis and stock returns, and we observe that kurtosis is positively related to the stock returns when the market is up and negatively related to the stock returns when the market is down. Both the estimated coefficients are significant at the $5 \%$ level of significance, which implies that similarly to skewness, kurtosis is an important factor. In models 6 through 9, as was mentioned already we study the relationships between stock returns and the various risk metrics, only this time we also consider the fact that the emerging and the developed stock markets might not be impacted the same by the various risk metrics. In all of these models, we observe pattern as in our earlier models, that is the estimated coefficients of the market betas are all significant at the $5 \%$ level of significance, and all the estimated coefficients for the oil prices are also significant at $10 \%$ level of significance, for both the emerging and the developed stock markets, taking into account up and down markets. The signs of the coefficients are also according to the theory, positive when we have an up market and negative when we have a down market. We do observe though that emerging stock markets appear to receive slightly higher risk premiums when the oil market is up than the developed stock markets.

In model 6, we observe that the estimated coefficients for the oil-supply risk aren't as significant as in the previous models. While the signs of the coefficient are according to the literature, we observe significant coefficients for the developed stock markets only when the market is up, and significant coefficients for the emerging stock markets only when the market is down. The interpretation is that the developed stock markets with higher betas receive higher risk premiums than low beta markets, but the same doesn't apply for the emerging stock markets.

Also, the interpretation for the emerging stock markets is that higher beta markets suffer greater losses in comparison to the low beta markets. In models 7,8 and 9 , we observe similar results with the ones of model 6 , with the coefficient of oil-supply risk being very significant for developed markets when the market is up at $5 \%$ level of significance, and with the coefficients of oil supply
risk for emerging stock markets when the market is down being significant at $10 \%$ level of significance.

In model 6, we also observe that that the estimated coefficient of the global oil demand risk is only significant in the developed stock markets and only when the market is up at $5 \%$ level of significance. In the previous models we also noticed that the coefficient of global oil demand is significant only when the market is up, but in this model we distinguish that emerging stock markets aren't influenced by it. These results are also robust across all models, as we observe similar results in models 7, 8 and 9. We also observe that the coefficients for the foreign exchange rate risk are not significant for neither the developed nor the emerging stock markets.

In model 7, we observe similar results to the previous models, as our estimated coefficients for the total risk are barely significant at $10 \%$ level of significance. More specifically, we observe that total risk is an important factor for the developed stock markets only when the market is up (positive relationship), and for the emerging stock markets only when the market is down. What is interesting though is that the coefficient of the total risk for the emerging stock markets when the market is down has a positive sign, which is contrary to theory, implying that high beta markets actually receive a higher positive premium than low beta markets when the markets are down. All in all, total risk doesn't seem to be a very significant role neither for the emerging nor the developed stock markets.

In model 8, we study the relationship between excess stock returns and skewness for the developed and emerging stock markets. We see that the estimated coefficient of skewness is negative for the developed and emerging stock markets when the market is up at the $10 \%$ level of significance. In down markets, the coefficient of skewness is positive and significant but only for the developed stock markets at the $5 \%$ level of significance. As we observe in model 4, skewness does appear to play a significant role, and especially in the case of developed stock markets.

The results of model 9 show that the estimated coefficients of kurtosis are positive when we have up markets for both the developed and emerging stock markets. More specifically, the coefficient of kurtosis is statistically significant at 5\% level of significance for the developed stock markets and statistically significant at $10 \%$ for the emerging stock markets. In down markets, the results
show a negative relationship between excess stock markets and returns but only in the case of developed countries at the $5 \%$ level of significance, while the coefficient for the emerging stock markets is insignificant.

Below we summarize the results of table 1.7 and 1.8. In all of our nine models the estimated coefficient of the world market risk has been found to be significant at the $5 \%$ level of significance and positive when we have up markets and negative when we have down markets. There doesn't appear to be any asymmetry in how developed and emerging stock markets are influenced. The coefficient for the oil price risk has also been found to be positive in up markets and negative in down markets, although it appears to be more significant in the emerging stock markets, and we also notice that the coefficients of the oil price risk are larger in the case of emerging stock markets than those of the developed stock markets.

In all of our 9 models, we've also observed that the coefficients of the exchange rate risk are insignificant. As far as the coefficients of the oil-supply risk are concerned, they are positively related to the stock returns and are significant at $5 \%$ level of significance but only for the developed stock markets, and negatively related to the stock returns when the market is down but only for the emerging stock markets. So it appears that oil-supply risk does play a role, but it isn't so significant.

In 4 of our models, the results show also a very significant relationship at $5 \%$ level of significance between stock returns and global oil demand risk but only when the markets are up and only for the developed stock markets.

Total risk is barely significant at $10 \%$ level of significance and it portrays a positive relationship to the stock returns when the market is up and a negative one when the market is down.

Finally, skewness has a significant relationship at $10 \%$ level of significance with the stock returns but seems to be significant only in the case of the developed countries, while we observe that kurtosis seems to play a role both in the developed and the emerging stock markets, although in the case of the emerging stock markets only when the market is up.

Table 1.7 Panel Regression Results from Risk Variables on Monthly Excess Stock Returns

| Variable | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Constant | $\begin{aligned} & -0,00878 \\ & (-1,634333) \end{aligned}$ | $\begin{aligned} & -0,008561 \\ & (-2,155069)^{*} \end{aligned}$ | $\begin{aligned} & -0,012488 \\ & (-3,056641) * \end{aligned}$ | $\begin{aligned} & -0,007109 \\ & (-1,733971)+ \end{aligned}$ | $\begin{aligned} & -0,008863 \\ & (-2,264716)^{*} \end{aligned}$ |
| Bm | $\begin{aligned} & -0,017873 \\ & (-2,316908)^{*} \end{aligned}$ |  |  |  |  |
| $\begin{aligned} & \mathrm{D} 1 \beta \mathrm{~m} \\ & (1-\mathrm{D} 1) \beta \mathrm{m} \end{aligned}$ |  | $\begin{aligned} & 0,036686 \\ & (6,497237)^{*} \\ & -0,027989 \\ & (-4,451044)^{*} \end{aligned}$ | $\begin{aligned} & 0,026417 \\ & (3,336996)^{*} \\ & -0,031635 \\ & (-3,239309)^{*} \end{aligned}$ | $\begin{aligned} & 0,032522 \\ & (5,529238)^{*} \\ & -0,022345 \\ & (-3,972679)^{*} \end{aligned}$ | $\begin{aligned} & 0,034676 \\ & (6,149159)^{*} \\ & -0,024667 \\ & (-4,079759)^{*} \end{aligned}$ |
| Bo | $\begin{aligned} & -0,017873 \\ & (0,164344) \end{aligned}$ |  |  |  |  |
| $\mathrm{D} 2 \beta \mathrm{o}$ |  | $\begin{aligned} & 0,076516 \\ & (4,46853) * \end{aligned}$ | $\begin{aligned} & 0,061019 \\ & (2,92685) * \end{aligned}$ | $\begin{aligned} & 0,068087 \\ & (4,071661) * \end{aligned}$ | $\begin{aligned} & 0,066844 \\ & (3,865338) * \end{aligned}$ |
| (1-D2)ßo |  | $\begin{aligned} & -0,060399 \\ & (-2,065557)^{*} \end{aligned}$ | $\begin{aligned} & -0,075559 \\ & (-2,354153) * \end{aligned}$ | $\begin{aligned} & -0,060215 \\ & (-2,201338)^{*} \end{aligned}$ | $\begin{aligned} & -0,065508 \\ & (-2,286064)^{*} \end{aligned}$ |
| Bex | $\begin{aligned} & -0,00618 \\ & (-1,99565) * \end{aligned}$ | $\begin{aligned} & -0,003461 \\ & (-1,27191) \end{aligned}$ | $\begin{aligned} & -0,00888 \\ & (-0,244146) \end{aligned}$ | $\begin{aligned} & -0,00297 \\ & (-1,103319) \end{aligned}$ | $\begin{aligned} & -0,002931 \\ & (-1,067743) \end{aligned}$ |
| $\overline{\mathrm{Bp}}$ | $\begin{aligned} & -0,000435 \\ & (-0,235488) \end{aligned}$ |  |  |  |  |
| $\begin{aligned} & \mathrm{D} 3 \beta \mathrm{p} \\ & (1-\mathrm{D} 3) \beta \mathrm{p} \end{aligned}$ |  | $\begin{aligned} & 0,003746 \\ & (1,830359)+ \\ & -0,004666 \\ & (-1,939632)+ \end{aligned}$ | $\begin{aligned} & 0,003512 \\ & (1,705094)+ \\ & -0,004905 \\ & (-2,05327)^{*} \end{aligned}$ | $\begin{aligned} & 0,004585 \\ & (2,400553)^{*} \\ & -0,004181 \\ & (-1,804222)+ \end{aligned}$ | $\begin{aligned} & 0,004056 \\ & (2,072745)^{*} \\ & -0,004618 \\ & (-1,992319)^{*} \end{aligned}$ |
| Bec | $\begin{aligned} & -0,08173444 \\ & (-0,941016) \end{aligned}$ |  |  |  |  |
| D4 $\beta$ ec <br> (1-D4) $\beta$ ec |  | $\begin{aligned} & 25,42429 \\ & (2,170356)^{*} \\ & -16,15132 \\ & (-1,611656) \end{aligned}$ | $\begin{aligned} & 24,90594 \\ & (2,140199) * \\ & -16,71018 \\ & (-1,566598) \\ & \hline \end{aligned}$ | $\begin{aligned} & 28,89954 \\ & (2,236059)^{*} \\ & -1,401946 \\ & (-1,283746) \end{aligned}$ | $\begin{aligned} & 28,07634 \\ & (2,229013) * \\ & -16,43747 \\ & (-1,522331) \\ & \hline \end{aligned}$ |
| D1TR (1-D1)TR |  |  | $\begin{aligned} & 0,213585 \\ & (1,908297)+ \\ & 0,130981 \\ & (0,903) \end{aligned}$ |  |  |
| D1SKEW <br> (1-D1)SKEW |  |  |  | $\begin{aligned} & -0,005691 \\ & (-1,983279)^{*} \\ & 0,012627 \\ & (2,743488) * \end{aligned}$ |  |
| D1KURT (1-D1)KURT |  |  |  |  | $\begin{aligned} & 0,002064 \\ & (3,97247)^{*} \\ & -0,001726 \\ & (-3,005247)^{*} \end{aligned}$ |
| Adjusted R-Squared F-Statistic D.W. Statistic | $\begin{aligned} & 0,012352 \\ & 10,8803 * \\ & 1,68279 \end{aligned}$ | $\begin{aligned} & 0,289765 \\ & 198,4189 * \\ & 1,914285 \end{aligned}$ | $\begin{aligned} & 0,290659 \\ & 162,4077 * \\ & 1,935795 \end{aligned}$ | $\begin{aligned} & 0,297768 \\ & 168,0297 * \\ & 1,940121 \end{aligned}$ | $\begin{aligned} & 0,295502 \\ & 166,2257 * \\ & 1,932242 \end{aligned}$ |

Notes: Cross Section Weights are used in Estimation |t-Statistics are reported in parentheses below the coefficients |
Heteroscedasticity consistent standard errors used in calculation of $t-$ stats $\mid *$ Denotes $p<0,05 \mid+$ Denotes $p<0.1 \mid$

Table 1.8. Panel Regression Results from Risk Variables on Monthly Excess Stock Returns

| Variable | Model 6 | Model 7 | Model 8 | Model 9 |
| :---: | :---: | :---: | :---: | :---: |
| Constant | $\begin{aligned} & -0,007683 \\ & (-2,035697) * \end{aligned}$ | $\begin{aligned} & -0,010196 \\ & (-2,62607)^{*} \end{aligned}$ | $\begin{aligned} & -0,007021 \\ & (-1,707881)+ \end{aligned}$ | $\begin{aligned} & -0,008088 \\ & (-2,057456) * \end{aligned}$ |
| Ddev D1 $\beta \mathrm{m}$ (1-Ddev) $\mathrm{D} 1 \beta \mathrm{~m}$ | $\begin{aligned} & 0,035141 \\ & (5,968059)^{*} \\ & 0,037775 \\ & (6,439772)^{*} \end{aligned}$ | $\begin{aligned} & 0,016375 \\ & (1,345922) \\ & 0,030302 \\ & (3,480944) \end{aligned}$ | $\begin{aligned} & 0,031733 \\ & (4,791835)^{*} \\ & 0,034016 \\ & (5,556591)^{*} \end{aligned}$ | $\begin{aligned} & 0,033158 \\ & (5,482773)^{*} \\ & 0,035206 \\ & (5,839754)^{*} \end{aligned}$ |
| $\operatorname{Ddev}(1-\mathrm{D} 1) \beta \mathrm{m}$ (1-Ddev) (1-D1) $\beta \mathrm{m}$ | $\begin{aligned} & -0,031349 \\ & (-4,898891)^{*} \\ & -0,023695 \\ & (-3,462431)^{*} \end{aligned}$ | $\begin{aligned} & -0,018994 \\ & (-1,450342) \\ & -0,033358 \\ & (-3,265231)^{*} \end{aligned}$ | $\begin{aligned} & -0,022014 \\ & (-3,822222)^{*} \\ & -0,021144 \\ & (-3,28883)^{*} \end{aligned}$ | $\begin{aligned} & -0,027851 \\ & (-4,415863) * \\ & -0,020649 \\ & (-3,159492) * \end{aligned}$ |
| Ddev D2ßo <br> (1-Ddev) D2ßo | $\begin{aligned} & \hline 0,065163 \\ & (2,207072)^{*} \\ & 0,069151 \\ & (4,176668)^{*} \end{aligned}$ | $\begin{aligned} & \hline 0,055457 \\ & (1,793228) \\ & 0,052914 \\ & (2,893591) * \end{aligned}$ | $\begin{aligned} & 0,057507 \\ & (1,99475)^{*} \\ & 0,062264 \\ & (3,774289) * \end{aligned}$ | $\begin{aligned} & \hline 0,055551 \\ & (1,926438) \\ & 0,06275 \\ & (3,498923) * \end{aligned}$ |
| Ddev (1-D2)ßo <br> (1-Ddev) (1-D2)ßo | $\begin{aligned} & -0,071676 \\ & (-1,867866)+ \\ & -0,065309 \\ & (-2,005872) * \end{aligned}$ | $\begin{aligned} & -0,082675 \\ & (-2,169829)^{*} \\ & -0,078799 \\ & (-2,32024)^{*} \end{aligned}$ | $\begin{aligned} & -0,065903 \\ & (-1,85301)+ \\ & -0,066845 \\ & (-2,198705) * \end{aligned}$ | $\begin{aligned} & -0,075727 \\ & (-2,06677)^{*} \\ & -0,066996 \\ & (-2,289772)^{*} \end{aligned}$ |
| Ddev Bex <br> (1-Ddev) Bex | $\begin{aligned} & \hline-0,00253 \\ & (-0,525872) \\ & -0,000389 \\ & (-0,135671) \end{aligned}$ | $\begin{aligned} & -0,000482 \\ & (-0,092333) \\ & 0,001543 \\ & (0,488843) \end{aligned}$ | $\begin{aligned} & -0,002577 \\ & (-0,526471) \\ & -0,000112 \\ & (-0,039091) \end{aligned}$ | $\begin{aligned} & -0,001384 \\ & (-0,290359) \\ & -0,000408 \\ & (-0,152098) \end{aligned}$ |
| Ddev D3ßp <br> (1-Ddev) D3ßp | $\begin{aligned} & \hline 0,005884 \\ & (2,04945)^{*} \\ & 0,00196 \\ & (0,904772) \end{aligned}$ | $\begin{aligned} & 0,006052 \\ & (2,195541) * \\ & 0,002304 \\ & (1,099898) \end{aligned}$ | $\begin{aligned} & 0,007763 \\ & (2,979325)^{*} \\ & 0,001793 \\ & (0,860369) \end{aligned}$ | $\begin{aligned} & 0,007061 \\ & (2,656703) \\ & 0,001832 \\ & (0,860041) \end{aligned}$ |
| Ddev (1-D3) $\beta$ p (1-Ddev) (1-D3) $\beta$ p | $\begin{aligned} & -0,005383 \\ & (-1,274015) \\ & -0,003613 \\ & (-1,687128)+ \end{aligned}$ | $\begin{aligned} & -0,005082 \\ & (-1,297142) \\ & -0,003608 \\ & (-1,69516)+ \end{aligned}$ | $\begin{aligned} & -0,003941 \\ & (-0,992602) \\ & -0,003947 \\ & (-1,915005)+ \end{aligned}$ | $\begin{aligned} & -0,004188 \\ & (-1,044138) \\ & -0,004024 \\ & (-1,940776)+ \end{aligned}$ |

Notes: Cross Section Weights are used in Estimation |t-Statistics are reported in parentheses below the coefficients |
Heteroscedasticity consistent standard errors used in calculation of $t-$ stats $\mid *$ Denotes $p<0,05 \mid+$ Denotes $p<0,1 \mid$
(Table continues in the Next Page)

Table 1.8. (Continued) Panel Regression Results from Risk Variables on Monthly Excess Stock Returns

| Variable | Model 6 | Model 7 | Model 8 | Model 9 |
| :---: | :---: | :---: | :---: | :---: |
| Ddev D4ßec | $\begin{aligned} & 49,06144 \\ & (2,1566)^{*} \end{aligned}$ | $\begin{aligned} & 48,0156 \\ & (2,048403) * \end{aligned}$ | $\begin{aligned} & 59,1742 \\ & (2,46276)^{*} \end{aligned}$ | $\begin{aligned} & 56,64782 \\ & (2,421754) * \end{aligned}$ |
| (1-Ddev) D4ßec | $\begin{aligned} & 14,84927 \\ & (1,388231) \end{aligned}$ | $\begin{aligned} & 16,82843 \\ & (1,547158) \end{aligned}$ | $\begin{aligned} & 14,16108 \\ & (1,276596) \end{aligned}$ | $\begin{aligned} & 14,04418 \\ & (1,250526) \end{aligned}$ |
| Ddev (1-D4)ßec | $\begin{aligned} & -23,39643 \\ & (-1,252401) \end{aligned}$ | $\begin{aligned} & -20,70392 \\ & (-1,149772) \end{aligned}$ | $\begin{aligned} & -13,23361 \\ & (-0,745025) \end{aligned}$ | $\begin{aligned} & -19,92391 \\ & (-1,111141) \end{aligned}$ |
| (1-Ddev) (1-D4)ßec | $\begin{aligned} & -9,868691 \\ & (-0,835091) \end{aligned}$ | $\begin{aligned} & -9,057741 \\ & (-0,69371) \end{aligned}$ | $\begin{aligned} & -12,36985 \\ & (-0,962028) \end{aligned}$ | $\begin{aligned} & -13,47554 \\ & (-1,042645) \end{aligned}$ |
| Ddev D1TR |  | $\begin{aligned} & 0,35118 \\ & (1,928869)+ \end{aligned}$ |  |  |
| (1-Ddev) D1TR |  | $\begin{aligned} & 0,142067 \\ & (1,458144) \end{aligned}$ |  |  |
| Ddev (1-D1)TR |  | $\begin{aligned} & -0,182536 \\ & (-0,823688) \end{aligned}$ |  |  |
| (1-Ddev) (1-D1)TR |  | $\begin{aligned} & 0,188776 \\ & (1,766819)+ \end{aligned}$ |  |  |
| Ddev D1SKEW |  |  | $\begin{aligned} & -0,00679 \\ & (-1,765679)+ \end{aligned}$ |  |
| (1-Ddev) D1SKEW |  |  | $\begin{aligned} & -0,00557 \\ & (-1,697524) \end{aligned}$ |  |
| Ddev (1-D1)SKEW |  |  | $\begin{aligned} & 0,016442 \\ & (3,246811) * \end{aligned}$ |  |
| (1-Ddev) (1-D1)SKEW |  |  | $\begin{aligned} & 0,006058 \\ & (0,895013) \\ & \hline \end{aligned}$ |  |
| Ddev D1KURT |  |  |  | $\begin{aligned} & 0,002542 \\ & (4,449929) * \end{aligned}$ |
| (1-Ddev) D1KURT |  |  |  | $\begin{aligned} & 0,001594 \\ & (1,786531)+ \end{aligned}$ |
| Ddev (1-D1)KURT |  |  |  | $\begin{aligned} & -0,0019 \\ & (-3,601234)^{*} \end{aligned}$ |
| (1-Ddev) (1-D1)KURT |  |  |  | $\begin{aligned} & -0,00173 \\ & (-0,924439) \end{aligned}$ |
| Adjusted R-Squared | 0,296079 | 0,295261 | 0,3022 | 0,299612 |
| F-Statistic | 101,3445* | 83,51688* | 86,29603* | 85,25309* |
| D.W. Statistic | 1,927833 | 1,94028 | 1,954047 | 1,945828 |

Notes: Cross Section Weights are used in Estimation |t-Statistics are reported in parentheses below the coefficients | Heteroscedasticity consistent standard errors used in calculation of $t$-stats $\mid *$ Denotes $p<0,05 \mid+$ Denotes $p<0,1 \mid$

## 6. Conclusion

While there have been many studies over the years on the relationship between stock markets and oil prices, most of these studies have concentrated solely on emerging or developed stock markets. This study was meant to explore the possible asymmetry between emerging and developed stock markets in how they are impacted by changes in the risk of oil.

In this study, an international multi - factor model was employed to study the relationship between stock market and oil price risk, using data of 22 stock markets, 11 of which were developed stock markets and 11 were emerging stock markets. Also to the best of our knowledge, this is the first time that Kilian's framework is combined with an international multi factor model. In this study, by acknowledging the fact that oil can't be treated as an exogenous variable and that it's important to account for the underlying reason that oil price increased, we also included proxies for oilsupply risk and global oil demand risk, in order to see what their relationships to the stock returns are. Moreover, in our models we also included other risk metrics such as skewness and kurtosis to observe how the emerging and developed stock markets are impacted by such risk measurements.

Our models showed that the relationship between excess stock returns and the market betas is significant in all of our models at $5 \%$ level of significance, while the relationship between stock returns and the coefficient of the oil price risk is significant in all of our models at 5\% and 10\% level of significance, and more specifically there is a positive relationship when we have up markets and a negative relationship when we have down markets.

No significant relationship was unveiled between the stock returns and the exchange rate risk in any of our models except one.

As far as the rest of the variables are concerned, we observed a significant relationship at 5\% level of significance between stock returns and oil-supply risk when the markets are up but only for the developed stock markets, and a significant relationship when the markets are down but only for the emerging stock markets.

The coefficient of the global oil demand risk seems to be significant at $5 \%$ level of significant but only for the developed stock markets and when the markets are up. Finally, from our results total risk doesn't seem to be an important factor, while skewness is significant but only for the developed stock markets. Both emerging and developed stock markets' returns seem to be impacted by kurtosis, although that's especially the case when we have an up market.

While the results that we reached were mostly correct according to the literature, as Sadorsky (2006) pointed out there is still room for improvement, as these relationships sometimes change depending on the frequency of the data that are used. Further studies should employ data with different frequencies in order to test for robustness.

Also, it's important to note that our results might be biased due to the fact that for our developed stock market dataset we used almost exclusively data from countries that belong to the European Union, while for the emerging stock market dataset we used data from countries all over the globe. The bias might arise from the fact that all of these countries are correlated with one another, and that they might have specific characteristics that are exclusive to the countries that belong to the European Union. Of course, as we mentioned in the beginning of this study, the selection of these stock markets was made partly due to unavailability of other data. So further studies should employ a greater set of stock markets from all around the globe to eliminate this possible bias.

## References

Abhyankar, A., Xu, B., \& Wang, J. (2013). Oil price shocks and the stock market: Evidence from Japan. Energy Journal, 34, pp. 199-222.

Aggarwal, R., Akhigbe, A., \& Mohanty, S.K. (2012). Oil price shocks and transportation firm asset prices. Energy Economics, 34, pp. 1370-1379.

Apergis, N., \& Miller, S.M. (2009). Do structural oil-market shocks affect stock prices? Energy Economics, 31(4), pp. 569-575.

Arouri, M. E. H. (2011). Does crude oil move stock markets in Europe? A sector investigation. Economic Modelling, 28, pp. 1716-1725.

Arouri, M. E. H., \& Rault, C. (2012). Oil prices and stock markets in GCC countries: Empirical evidence from panel analysis. International Journal of Finance and Economics, 17, pp. 242-253.

Asteriou, D., \& Bashmakova, Y. (2013). Assessing the impact of oil returns on emerging stock markets: A panel data approach for ten Central and Eastern European countries. Energy Economics, 38, pp. 204-211.

Bali, T.G., Cakici, N., \& Whitelaw, R.F. (2011). Maxing out: Stocks as lotteries and the cross section of expected returns. Journal of Financial Economics, 99(2), pp. 427-446.

Basher, S.A., \& Sadorsky, P. (2006). Oil price risk and emerging stock markets. Global Finance Journal, 17(2), pp. 224-251.

Basher, S. A., Haug, A.A., \& Sadorsky, P. (2012). Oil prices, exchange rates and emerging stock markets. Energy Economics, 34(1), pp. 227-240.

Bastianin, A., Conti, F., \& Manera, M. (2016). The impacts of oil price shocks on stock market volatility: Evidence from the G7 countries. Energy Policy, 98, pp. 160-169

Bekaert, G., \& Harvey, C.R. (1995). Time varying world market integration. Journal of Finance, 50, 403-444.

Bekaert, G., \& Harvey, C. R. (1997). Emerging equity market volatility. Journal of Financial Economics, 43, pp. 27-77.

Bjornland, H. C. (2009). Oil price shocks and stock market booms in an oil exporting country. Scottish Journal of Political Economy, 56(2), pp. 232-254.

Black, F. (1972). Capital Market Equilibrium with restricted borrowing. Journal of Business, 45, pp.445-455

Broadstock, D.C., \& Filis, G. (2014). Oil price shocks and stock market returns: New evidence from the United States and China. Journal of International Financial Markets, Institutions \& Money, 33, pp. 417-433.

Brealey, R., \& Myers, S. (2003). Principles of corporate finance ( $7^{\text {th }}$ Edition). McGraw Hill
Campbell, J.Y., Lo, A., \& MacKinlay, A.C., (1997). The Econometrics of Financial Markets. Princeton NJ Princeton University Press

Chang, K. L., \& Yu, S. T. (2013). Does crude oil price play an important role in explaining stock return behavior? Energy Economics, 39, pp. 159-168.

Chang, K. L., Christoffersen, P., \& Jacobs, K. (2013). Market skewness risk and the cross section of stock returns. Journal of Financial Economics, 107, pp.46-68

Chen, N.F., Roll, R., \& Ross, S.A. (1986). Economic forces and the stock market. Journal of Business, 59, pp. 383-403.

Choi, K., \& Hammoudeh, S. (2010). Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment. Energy Policy, 38, 4388-4399.

Cong, R.G., Wei, Y.M., Jiao, J.L., \& Fan, Y. (2008). Relationships between oil price shocks and stock market: An empirical analysis from China. Energy Policy, 36, pp. 3544-3553.

Cunado, J., \& de Gracia, F.P. (2014). Oil price shocks and stock market returns: Evidence for some European countries. Energy Economics, 42, pp. 365-377.

El-Sharif, I., Brown, D., Nixon, B., \& Russell, A. (2005). Evidence on the nature and extent of the relationship between oil prices and equity values in the UK. Energy Economics, 27, pp. 819-830.

Elyasiani, E., Mansur, I., \& Odusami, B. (2011). Oil price shocks and industry stock returns. Energy Economics, 33, pp. 966-974.

Gallegati, M. (2012). A wavelet-based approach to test for financial market contagion. Computational Statistics and Data Analysis, 56, 3491-3497

Güntner, J. H. (2014). How do international stock markets respond to oil demand and supply shocks? Macroeconomic Dynamics, 18(8), pp. 1657-1682.

Fama, E., \& MacBeth, J.D. (1973). Risk, return and equilibrium: Empirical Results. Journal of Political Economy, 71, pp. 607-636

Faff, R.W., \& Brailsford, T.J. (1999). Oil price risk and the Australian stock market. Journal of Energy Finance and Development, 4, pp. 69-87.

Ferderer, J.P. (1996). Oil Price Volatility and the Macroeconomy. Journal of Macroeconomics Vol.18, No. 1, pp. 1-26

Ferson, W.W., \& Harvey, C.R. (1994). Sources of risk and expected returns in global equity markets. Journal of Banking and Finance, 18, pp.775-803

Filis, G., Degiannakis, S., \& Floros, C. (2011). Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries. International Review of Financial Analysis, 20(3), pp. 152-164.

Hamao, Y. (1989). An empirical examination of the arbitrage pricing theory: Using Japanese data. Japan and the World Economy, 1, pp. 45-61.

Hamilton, J.D. (1983). Oil and the Macroeconomy since World War II. Journal of Political Economy, Vol.91, No. 2 (Apr., 1983), pp. 228-248

Hamilton, J. D. (2003). What is an oil shock? Journal of Econometrics, 113, pp. 363-398.

Hamilton, J.D. (2009a). Causes and consequences of the oil shock of 2007-08. Brookings papers on economic activity. Spring, pp. 251-261.

Hammoudeh, S., \& Aleisa E. (2008). Dynamic Relationships among GCC Stock Markets and Nymex Oil Futures. Contemporary Economic Policy, Vol. 22(2), pp. 250-269

Harvey, C.R., \& Siddique, A. (2000). Conditional skewness in asset pricing tests. Journal of Finance, 55, pp. 1263-1295.

Huang, R. D., Masulis, R.W., \& Stoll, H. R. (1996). Energy shocks and financial markets. Journal of Futures Markets, 16, pp. 1-27.

Jones, C.M., \& Kaul, G. (1996). Oil and the stock markets. Journal of Finance, 51, pp. 463-491.
Kilian, L. (2008). Exogenous oil supply shocks: How big are they and how much do they matter for the US economy? The Review of Economics and Statistics, 90, pp. 216-240.

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. American Economic Review, 99(3), pp. 1053-1069.

Kilian, L., \& Park, C. (2009). The impact of oil price shocks on the US stock market. International Economic Review, 50(4), pp. 1267-1287.

Lee, B.R., Lee, K., \& Ratti, R.A. (2001). Monetary Policy, oil price shocks, and the Japanese Economy. Japan and the World Economy, Vol. 13, Issue 3, pp. 321-349

Nandha, M., \& Faff, R. (2008). Does oil move equity prices? A global view. Energy Economics, 30(3), pp. 986-997.

Narayan, P.K., \& Narayan, S. (2010). Modelling the impact of oil prices on Vietnam's stock prices. Applied Energy, Vol. 87, pp. 356-361

Narayan, P. K., \& Sharma, S. S. (2011). New evidence on oil price and firm returns. Journal of Banking \& Finance, 35(12), pp. 3253-3262.

Martin-Barragan, B., Ramos, S.B., \& Veiga, H. (2015). Correlations between oil and stock markets: A wavelet-based approach. Economic Modelling, 50, pp. 212-227.

Miller, J. I., \& Ratti, R. A. (2009). Crude oil and stock markets: Stability, instability, and bubbles. Energy Economics, 31(4), pp. 559-568.

Mo, X., Su, Z., \& Yin, L. (2019). Can the Skewness of oil returns affect stock returns? Evidence from China's A-Share markets. North American Journal of Economics and Finance, 50

Mohaddes, K., \& Pesaran, M. H. (2017). Oil prices and the global economy: Is it different this time around? Energy Economics, 65, pp. 315-325.

Mohanty, S.K., Nandha, M., Turkistani, A.Q., \& Alaitani, M.Y. (2011). Oil price movements and stock market returns: Evidence from Gulf Cooperation Council (GCC) countries. Global Finance Journal, 22, pp. 42-55.

Mollick, A.V., \& Assefa, T.A. (2013). US stock returns and oil prices: The tale from daily data and the 2008-2009 financial crisis. Energy Economics, 36, pp. 1-18.

Mork, K.A. (1989). Oil and the Macroeconomy when prices go up and down: An extension of Hamilton's results. Journal of Political Economy, 97(3), pp. 740-744.

Nandha, M., \& Hammoudeh, S. (2006). Systematic risk, and oil price and exchange rate sensitivities in Asia-Pacific stock markets. International Business and Finance, 21, pp. 326-341

Papapetrou, E. (2001). Oil price shocks, stock market, economic activity and employment in Greece. Energy Economics, 23, 511-532.

Park, J., \& Ratti, R. A. (2008). Oil price shocks and stock markets in the US and 13 European countries. Energy Economics, 30(5), pp. 2587-2608.

Peng, C., Zhu, M.M., Jia, X.H., \& You, W.H. (2017). Stock price synchronicity to oil shocks across quantiles: Evidence from Chinese oil firms. Economic Modelling, 61, 248-259.

Pettengill, G., Sundaram, S., \& Mathur, I. (1995). The conditional relation between beta and return. Journal of Financial and Quantitative Analysis, 30, pp. 101-116

Rapaport, A. (2013). Supply and demand shocks in the oil market and economy-wide shocks that affect asset prices. Chicago Booth Research Paper.

Sadorsky, P. (1999). Oil price shocks and stock market activity. Energy Economics, 21, pp. 449-469.

Sadorsky, P. (2001). Risk factors in stock returns of Canadian oil and gas companies. Energy Economics, 23, pp. 17-28.

Salisu, A.A., \& Isah, K.O. (2017). Revisiting the oil price and stock market nexus: A nonlinear panel ARDL approach. Economic Modelling, 66, pp. 258-271.

Shapiro, A.C. (2003). Multinational financial management (seventh edition). New York John Wiley \& Sons.

Silvapulle, P., Smyth, R., Zhang, X., \& Fenech, J.P. (2017). Nonparametric panel data model for crude oil and stock prices in net oil importing countries. Energy Economics, Vol. 67, pp. 255-267.

Smyth, R., \& Narayan, P.K. (2018). What do we know about oil prices and stock returns? International Review of Financial Analysis, 57, pp. 148-156

Wang, Y., Wu, C., \& Yang, L. (2013). Oil price shocks and stock market activities: Evidence from oil-importing and oil-exporting countries. Journal of Comparative Economics, 41, pp. 1220-1239.

