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An investigation into the relationship between political and country risk the implied volatility contained within oil option contracts.

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Abstract

The global crude oil market, today still greatly important to the global economy, is characterized by a small number of countries exporting and importing great amounts of crude oil, some of these countries being OPEC members. Country-specific and political events in these countries relevant to the global crude oil market have had sizable consequences for the global crude oil market. This thesis investigates the relationship between country- & political risk in these oil-relevant countries, and price of crude oil, and the IV of crude oil options contracts. A GARCH analysis modeling crude oil price and crude oil options implied volatility as a function of composite country political risk scores of several subcategories of countries, such as OPEC, OPEC+, non-OPEC oil exporters and non-OPEC oil importers yields mixed results, with some indication for a negative relationship between country risk in OPEC countries and the price of crude oil and implied volatility in crude oil options contracts. Mixed, but statistically significant results are yielded for the other categories included. The mixed results suggest the complexity of the focal relationships, and imply directions for future research.

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The views stated in this thesis are those of the author and not necessarily those of the supervisor, second assessor, Erasmus School of Economics or Erasmus University Rotterdam.

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1 Introduction and Literature

1.1 Country and political risk

1.1.1 The importance of risk in asset pricing

The proverb "Do not put all your eggs in one basket" is a great example for understanding the concepts of risk and diversification benefits in a real-world application. However, risk does not only exist in the world of eggs, but is also one of the most important concepts in the financial world, and greatly determines the success of investments of all kinds. Therefore, carefully studying the risks embodied in an investment can give an investor a good view on the potential fluctuations in the value of his investment and thus the potential up- and downside associated with this investment. Properly understanding the up- and downside potential together with the risk profile of an investment can then give investors an accurate approximation of the value of an investment opportunity and thus the price an investor is willing to pay for the investment asset. This is especially important in the context of financial markets, where a large number of investors have the shared opportunity of buying and selling financial assets. When an investor finds that his value approximation on an asset is different from the value implied by the consensus price within a market, then there exists an investment opportunity as the investor is then able to acquire (sell) the asset and its potential upside for a price that is relatively lower (higher) than what would be a fair price according to the investors' value approximation. As such, investors are continuously trying to improve their financial models to get the most accurate estimation of an asset's value and predict future fluctuations in the asset's value, which could then allow acting on asset mispricing by the market. Examples of these financial models are plentiful, such as the Capital Asset Pricing Model (CAPM), the Fama-French three-factor model, and the Carhart four-factor model, and they all aim to accurately and consistently explain returns on financial assets. However, since all these models try to model the essentially stochastic movement of financial markets, they often fail to accurately or consistently explain stock market returns, which gives rise to attempts to create new financial models that are meant to improve on the existing ones. An example of this movement to accurately model stock market returns is the previously mentioned Carhart four-factor model, which was an attempt to improve on the Fama-French three-factor model by including an additional factor in the model that captures the momentum of changes in an asset's market price (Carhart, 1997). Risk is also important and present in these financial models through variables such as the commonly known β in the CAPM, but the concept of risk is also included in the parameter representing the risk free rate. In the example of the CAPM being used, the β coefficient is a measure of to what degree the focal asset moves compared to the overall market's returns, or its "inherent" volatility. As such, an asset's β can also be understood as the systematic and thus non-diversifiable risk of adding the asset to an investment portfolio. However, since this systematic volatility includes both up- and down-movements, high β assets are generally also the ones that achieve the highest returns, thus thoroughly intertwining the concepts of risk and return. Therefore, when evaluating investment opportunities, one cannot look at returns without evaluating the risk that accompanies the investment, or vice versa. This becomes especially important in the context of predetermined risk appetites, for example in the case of investment mandates that set specific levels of risk that are not to be exceeded in a portfolio, which is common practice in the fields of investment banking and institutional asset management (e.g. pension funds). One recent example demonstrating the importance of the joint consideration of risk and return is the subprime mortgage crisis of 2007 which was a great contributor to the 2007 global financial crisis. This crisis came after a period of strong global economic growth, which led investors to chase ever higher returns without properly considering the potential downside of these high returns, namely the risk that accompanied them. Indeed, after the occurrence of the crisis, the G20 leaders, in their *Declaration of the Summit on Financial Markets and the World Economy* (n.d.) stated that the period preceding the start of the crisis was characterized by

> "market participants [seeking] higher yields without an adequate appreciation of the risks and failed to exercise proper due diligence."

which was determined to be one of the root causes of the crisis outbreak. Considering the severe consequences of this crisis, it becomes clear that proper consideration of the relationship between risk and return is crucial, not only for individual market participants but also for national governments and other bodies governing the financial markets.

1.1.2 The importance of risk for institutions and governments

Before one can properly investigate the concept of risk in any type of market, it is very worthwhile to consider the history of the concept of risk in financial markets, and how the role of risk has evolved in our modern history. This will provide the necessary context and considerations related to risk in markets. Doing so will provide a conceptual foundation for the research direction of this paper and will introduce the aspect of practical implications associated with this research direction.

Since the inception of financial markets, they have gradually become more interlinked with the real economy and everyday life, to a point where changes in financial markets can have very real effects on society. One of the earliest examples of this connection is the infamous Wall Street stock market crash of 1929, after which a downturn in the financial markets manifested itself into an economy-wide slowdown, coupled with increases in unemployment. The bursting of the dot-com bubble in 2001 led to the failure of many IT businesses, the evaporation of huge portions of market capitalization for businesses such as Cisco (Powell, 2021) and Amazon.com, and consequently resulted in mass layoffs in the technology industry. Similarly, the financial crisis of 2007-2008, which occurred after the bursting of the housing bubble, resulted in bank failures and a period of global economic slowdown, which has now been coined as the "Great Recession". During this Great Recession, onset by occurrences in financial markets, some countries experienced a huge decrease in economic output, increases in unemployment and many other related costs (Atkinson, Luttrell, & Rosenblum, 2013) which greatly affected their inhabitants. The financial markets and real economies are linked to and related to each other due to the inherent overlap in these two contexts. Risk is present in both of them and, even though it takes on different forms, is a factor in both of them and also functions similarly in both of these contexts, as in both contexts risk is comprised of a β denoting the systematic risk which can eventually influence some monetary outcome. Besides the overlap in risk between these two contexts, the two contexts are also linked to each other because of capital streams flowing from the real economy to financial markets and vice versa. Because of the presence of risk in both these contexts and the interrelatedness of these contexts, governments and other governing bodies have been creating and optimizing integrated policies, which are aimed at ensuring the stability of financial markets and countries' financial institutions. These policies are typically aimed at improving the stability of the financial institutional environment by ensuring that risk is properly considered and accounted for. Additionally, they are aimed at ensuring that institutions are adequately "cushioned" against the immediate effects of these risks and are thus able to withstand periods of stress without failing, which in many cases would have grave consequences for society as these institutions typically fulfill functions that are important to our everyday life, e.g. facilitating transactions and providing retirement. Examples of such policies are those policies implemented by governing financial organizations, such as the Federal Reserve of the United States, and the European Central Bank (ECB). The ECB names these policies as being "macroprudential". These macroprudential policies are then aimed at limiting the built-up risk, smoothing financial cycles over time, increasing the resilience of the European financial environments, and setting prudential investment goals for individual market participants, as outlined in their report named *Financial stability and macroprudential policy* (n.d.). One common example of these policies is the setting of minimum capital requirements for national banks so that they are better protected against shocks, which also has been a recurring subject in the Basel Accords. Over the years, the efforts to limit the dangers of financial risk in crucial parts of our economies have been improved and intensified, and further integrated between economies.

1.1.3 Financial risk and the evolution of consideration of risk

According to the specific context, there exist many different possible definitions for the concept of risk. The definition of financial risk is generally understood as the probability of actual returns on any type of investment being different from the expected return and also includes those cases in which this probability of financial losses is not properly understood. This definition can then be extended to any asset in which agents can invest and that is valued by financial markets and its participants or is otherwise subject to valuation. Inherently, there are many different reasons for an asset to realize returns that differ from the expected level of returns, which are generally conceptualized as belonging to several distinct categories of financial risk. The most important of these financial risk categories include but are not limited to market risk (risk of the market valuation of an asset fluctuating), liquidity risk (risk of the market not having enough liquidity for the asset holder to trade his asset quickly enough to prevent realizing negative returns), counterparty credit risk (risk of a counterparty in any transaction defaulting and not being able to honor the agreement) and operational or business risk (risk of realizing losses greater than the expected level of losses). It is interesting to note that the current categorization and understanding of relevant risks has not always been in place, as throughout the 20th century an increasing number of sources of financial risk has been identified and deemed important enough to include in financial policy and financial risk management practices. This evolution of charting risk can be seen clearly in the evolution of the Basel Accords which have been set in place mainly for the supervision of financial institutions. The first Basel Accord had been established in 1988 and considered several distinct sources of financial risk that were used to determine the capital requirements for banks. Since then, the Basel Accord has evolved into the current Basel III Accord, which had been decided upon in 2010, with each (sub)version of the accord considering more sources of financial risk that were deemed significant to the success and survival of banks (Dionne, 2013).

Even though the sources of financial risk included in the original Basel Accords may seem obvious, other sources of financial risk are less obvious, yet could represent an important portion of the overall risk embodied in an investor's holdings. One of these sources of financial risk is the so-called country risk. Country risk has become significantly more important to consider because of the globalization of financial markets and the growing linkages between the economies of the world, which has partly been a consequence of advancements in communication technology. This globalization trend has enabled capital flows to previously isolated economies and has thus enabled (foreign) investment into these countries. However, the spreading of investors' holdings to other economies and political environments also brings additional risks into the equation that need to be considered. An obvious source of risk introduced by international investing is the risk pertaining to currency exchange, where an investor's holdings are affected by the exchange rate between the investor's home currency and the currency of his holdings. However, there are also risks stemming from the business environment of the country of investment. The sum of all these risks is commonly referred to as overall country risk, or the overall risk that is embodied in investments in a specific country.

1.1.4 Financial risk, business risk, country risk and political risk.

Within the plethora of different sources of financial risk, business risk is one of the main sources that impose risk on organizations and has been defined by Van Horne and Wachowicz (2009) as being "the risk inherent in the firm, independent of the way it is financed (pp. 207-208)", and thus imposes uncertainty on the performance of a firm. As such, business risk constitutes those sources of risk that affect the business environment of a firm, and with it the subsequent performance of the firm, as this is ultimately greatly determined by the business environment it operates in. This business environment consists of many individual factors that affect the business and its operations, and many types of categorizations have been proposed. Two of the most well-known examples of these categorizations are Porter's five forces model (Porter, 1979) and the PEST analysis (Political, Economic, Socio-Cultural, and Technological) framework. Where Porter's five forces model mostly focuses on a firm's direct business environment in the shape of its specific operating industry, the PEST analysis framework is scoped beyond that, also including non-economic factors. This notion, that non-economic factors can also play an important role in affecting business operations, is becoming evermore important, with trends such as non-financial reporting, corporate social responsibility, and environmental concerns (which has been included in the more elaborate

PESTLE analysis framework).

This country risk can be specified further into economic risks, political risks and financial risks. While economic risk and financial risk are generally well-known and extensively documented, likely due to their direct and immediate effects on the business environment, political risk tends to receive less attention. Consequently, economic and financial risks are often investigated in isolation from political risks, even though the risk stemming from the political climate could potentially have significant consequences for businesses' operations as well. Especially with the upward trend in foreign investment, it could be very worthwhile to further investigate the dynamics and the implications of political risk for financial agents, with Dymsza (1972) noting that a firm's political environment and the political risk associated with it is indeed a noteworthy source of significant business risk. Therefore, this paper will delve further into the importance of the whole of country risk, considering economic, financial and political risks jointly.

Weston and Sorge (1972) have defined political risk as being those risks that "arise from the actions of national governments which interfere with or prevent business transactions, or change the terms of agreements, or cause the confiscation of wholly or partially foreign-owned business property" (p. 60). Robock (1971) further specifies the definition of political risk, stating that political risk only exists when the business environment is subject to discontinuities that stem from a change in the political environment and are difficult to anticipate. Additionally, he posits that these changes in the political and business environment can only be considered a risk when they "have the potential for significantly affecting the profit or other goals of a particular enterprise" (p. 7). He, therefore, makes a distinction between general political instability and actual instances of political risk, stating that the first is continuous and the latter is discontinuous and constitutes sudden changes. An example of changes in the political environment that did not source political risk is given by Fitzpatrick (1983), where he mentions the example of Italy undergoing 40 significant governmental changes in a time period of just 36 years. These changes in the political environment, however, did not bring about significant business risks. Another notion that Robock (1971) makes is the distinction between micro and macro-political risk, where macro-political risk is defined as being "unanticipated and politically motivated environmental changes [which] are broadly directed at all foreign enterprise" and micro-political as "the environmental changes [that] are intended to affect only selected fields of business activity or foreign enterprises with specific characteristics" (p.9).

Specific sources and examples of political risk can be seen saliently in our modern-day global society. Political risk, for example, includes risk stemming from changes to the business environment caused by policies instated by institutions such as national governments. For instance, a country's government could opt to change their corporate tax policies, or directly restrict foreign investments. More severe examples of sources of political risk are scenarios in which the country of investment is invaded by another sovereign (such as the Gulf War of 1990), is subject to a rebellion or coup d'état (as was the case in the Arab Spring of 2010), or is otherwise punished with sanctions (Russia after the 2022 invasion of Ukraine). However, what all these instances had in common was the fact that the changes in the political environment had severe consequences for the business environment in the relevant economies. The Gulf War of 1990 proved to be a major event with regard to the political dynamics in the Middle East and also bared highly interesting insights into the dynamics of the global crude oil market and its behaviour in times of geopolitical stress. Additionally, it also had major consequences for many national economies through the effects on the global oil market, baring the importance of oil and its derivatives for sustaining economies and societies (Lieber, 1992). This demonstrated the importance of understanding the linkage between crude oil markets and the political environments in countries that are major players in those markets. These instances of political risk affecting economies are not limited to the real economy but also affect the financial markets. Indeed, the financial markets react to and consider political factors that could impose political risk. For example, Goodell and Vähämaa (2013) shows that the stock price implied volatility reacts to news surrounding the U.S. presidential election, which one can imagine to imply significant changes in the political environment.

1.2 The dynamics of the global oil commodity market

1.2.1 The intertwining of the oil commodity market and global economy

The political risk previously discussed has far-reaching influences on investments and assets of all types. One of the assets that political risk greatly affects, is the commodity class of assets. Since the earliest societies and nations, a country's natural resource endowment and its ability to extract crucial commodities (e.g. coal, precious metals, fossil fuels, grain) from this natural resource endowment have been a crucial factor for the given country's economic development, with some commodities playing more important roles than others. However, the natural resource endowments differ greatly across nations, thus resulting in scenarios where a country is an exporter of a crucial commodity that it has been oversufficiently endowed with and an importer of crucial commodities that it lacks. The resulting interactions between these exporting and importing countries result in a peculiar market setting, with some countries being dependent on imports of a crucial commodity, and some exporting countries potentially becoming reliant on the rents generated from the commodity exports. Furthermore, the reliance on commodities also stretches to the plane of geopolitics, with nations trying to ensure that they have access to these crucial commodities. As a result, reliance on commodities and a nation's endowment with these commodities is a very common source of scenarios in global geopolitics. Since commodities (and the demand and supply sides of the commodity market) are often the subject of geopolitics or affected by geopolitics, important geopolitical events can have far-reaching consequences on the dynamics of the global commodity markets. As an example, after the Russian invasion of Ukraine in 2022 (which is a major producer and exporter of wheat) the price of wheat increased greatly following the decrease in supply caused by the decrease in wheat production in Ukraine, thus influencing food prices in countries globally. Besides geopolitics, national politics can also have an influence on commodity markets. This could occur in the context of national governments implementing policies aimed at stimulating the production or import of a commodity, which in turn influences the global commodity market through supply and demand. As a result of the influence of politics and geopolitics on commodity markets, investors that act in these commodity markets need to be aware of the possibility of commodity price fluctuations caused by politics, thus introducing the importance of political risk in commodity markets.

One such commodity, which is crucial to our modern economy and also heavily influenced by political risk, is crude oil and its derivatives. In recent times there has been an ever-growing movement to step away from fossil fuels as our main energy source and move towards energy sources that do not rely on depletable natural resources. This movement has been gaining more traction over time due to the growing concerns over climate change and the fact that these natural resources will inevitably run out in the future. However, in recent times it has been salient that these natural resources can also be of great political importance, as these resources are mostly exported by a few countries in the world. This political importance of fossil fuels greatly relies on the fact that, despite the growing sentiment to move away from fossil fuels as an energy source (Dunz, Monasterolo, & Raberto, 2018; Erickson, Lazarus, & Piggot, 2018; Ayling & Gunningham, 2017; Lazarus & van Asselt, 2018), the global and national economies still greatly rely on fossil fuels. This reliance is especially evident in the energy industry and the transport industry, which are both greatly important for a nation's economy. This is demonstrated by the fact that in 2019 approximately 84% of the world's primary energy was sourced from fossil fuels, such as coal, oil, and gas. Additionally, in 2021 many significant global economies such as Japan, Italy, and the United States all sourced over 80% of their primary energy from fossil fuels (Ritchie, Roser, & Rosado, 2022). Historically, shocks in the fossil fuel market, which on multiple occasions have been triggered intentionally by important oil exporters or importers, have been shown to significantly affect economies and their populations, thus showing the potential of employing oil as a political measure. The earliest significant example of oil being used as a political weapon goes back to the year 1956 when during the Suez Crisis some crucial oil pipelines were destroyed in order to disrupt the French and British invading forces attempting to capture the Suez Canal. The consequent disruption in oil supply significantly affected the overall oil supply to all countries of the western part of Europe, thus proving to be a relatively effective measure (Ahrari, 2014). In 1973, the exclusively Arab version of the OPEC, the Organization of Arab Petroleum Exporting Countries (AOPEC), initiated an oil embargo against the countries that supported Israel during the Yom Kippur War of 1973, which included nations such as the United States, the United Kingdom, Japan, and the Netherlands. This embargo, which involved a huge price increase and a decrease in the global oil supply led to the global price of oil increasing with almost 300% (Schumacher, 1985), and the oil price in the countries specifically targeted by the embargo skyrocketing by much more than that. Shortly thereafter, another oil shock took place, coined the 1979 Oil Shock, or the Second Oil Crisis. This crisis was directly caused by the 1978 Iranian Revolution, which saw the Pahlavi government replaced by the Islamic Republic, ruled by Ayatollah Khomeini (Chalcraft, 2016). This period of political unrest in Iran, which is a major oil exporting country, saw the world production of crude oil decrease by 7 percent (Graefe, 2013). This resulted in crude oil prices increasing by over 160% from 1979 to 1980, resulting in significant export gains for some other OPEC countries (Gross, 2019). As demonstrated, our modern-day economy and the industries that drive it are still heavily reliant on fossil fuels as an energy source. Even though many new initiatives are aimed at reducing the dependence on fossil fuels and instead moving to renewable and sustainable energies, the International Energy Agency has projected that this reliance is very unlikely to disappear any time soon (Gould & Kim, 2019). As such, the extraordinary role that oil as a commodity has played in the last century will likely continue to be significant and important to consider. While the reliance on oil is unlikely to disappear and with the global fossil fuel reserves slowly being depleted, the global oil market is sure to undergo some drastic changes, both on the demand/import and supply/export sides of the market, but also the dynamics in foreign relations that are a result of these two sides of the global oil market. As such, any findings of this paper on the influence of political risk on the global oil market could have significant implications for market agents in the short run, but also in the long run where the market dynamics may be subject to change. However, the reliance on fossil fuels is not only present on the demand side of the market. Some (mostly developing) countries on the supply side of the market are heavily reliant on the oil rents that their oil production yields their economy for economic development, with countries such as Iraq, the Republic of Congo, and Kuwait generating more than 30% of their annual GDP through oil rents (*Oil rents as % of GDP*, n.d.) in the year 2020, and many other countries also generating significant shares of their GDP through oil rents. With such a large share of their economy dependent on oil rents, such countries are heavily dependent on the oil market and oil prices, as these directly influence the value they can generate through oil exports. Additionally, Fatai, Cheol, Muhammad, et al. (2017) have shown that, for their sample of oil-dependent countries (which largely coincides with the focal countries of this paper), oil rents significantly affect countries' fiscal balance. Moreover, Gaddy and Ickes (2005) shows the link between oil rents and the overall economic performance of Russia, which has historically been one of the largest oil exporters in the world. In the case of these oil-exporting, and in some cases oil-dependent countries, the role oil rents play in financing the state and public investment can be beneficial, but also detrimental when the dependency on oil rents is too severe. As such, the scenario of a sharp decrease in the global oil price would have disastrous consequences for these countries and could severely limit economic development, at least in the short term. As these countries are economically reliant on the global oil market, any insights into and understanding of the factors that influence the global oil market could greatly help these countries with foreseeing fluctuations in crucial export rents.

1.2.2 The influence of OPEC

As mentioned, the Organization of Petroleum Exporting Countries (OPEC) has been an important player in the global oil sector since its inception in 1960, and by extension also in global politics. It has great influence in the oil sector through its role as a cooperative organization of countries that account for 80.4% of the global oil reserves proven to exist (*OPEC share of World Crude Oil Reserves*, n.d.). Additionally, countries that belong to OPEC account for approximately 40% of the global crude oil production, and OPEC member countries' oil exports also account for approximately 60% of the total international trade in petroleum (*What drives crude oil prices?*, n.d.). These numbers clearly show the highly significant role the OPEC can play in influencing the global oil market. This influence has also been investigated in academics, with Deaves and Krinsky (1992) showing that the prices of crude oil options contracts fluctuate as a result of the outcomes of OPEC meetings, and Horan, Peterson, and Mahar (2004) demonstrating that the implied volatility of crude oil options prices significantly fluctuates before, during and after OPEC meetings. As such, OPEC decisions do not only directly affect the oil market, but also the derivative contracts market for oil. However, the reach of OPEC decisions is not limited to just its members. Firstly, there exists a group of countries called OPEC+, which can be seen as a group of petroleum exporting countries that voluntarily cooperate with OPEC initiatives, as they recognize that they have incentives to do so. Secondly, there is also a group of countries that are not members of OPEC or OPEC+. These countries generally attend official OPEC meetings by sending national representatives to these meetings with the goal of aligning their policies with the decisions made by OPEC. Finally, it can be said that every major oil exporter in the world is affected by OPEC and its decisions, either by being a direct OPEC member, being part of the OPEC+ group, by aligning their policies through the aforementioned "observers", or simply by (involuntarily) being affected by the effects that OPEC decisions have on the global oil market. The aforementioned subcategories of oil exporting countries have all been focused on the exporting or the supply side of the global crude oil market. However, since any market is made by both a supply and a demand side, it could also be very worthwhile to take a look at countries that report significant oil imports. Therefore, one final subcategory of countries will be included in the analysis. This subcategory will comprise of the 10 countries with the largest average crude oil imports by barrels of crude oil imported per day (*EIA International Crude Oil Imports*, n.d.) over the years 2012-2022. The major oil exporting and importing countries have thus been categorized into several subcategories [1], as can be seen in table 1.

[1]The countries in the Non-OPEC exporters and Importers subcategories as shown in table 1 have been selected based on their national annual export and import numbers respectively. It should be noted that the exports and imports of crude oil in some countries (such as the UK) are also partly facilitated through private companies which could result in differences between a country's actual crude oil exports and imports and the reported national crude oil exports and imports.

Table 1: Subcategories of oil exporting and importing countries

OPEC (13)	**OPEC + (10)**	**Exporters (5)**	**Importers (10)**
Algeria	Azerbaijan	Brazil	USA
Angola	Bahrain	Canada	China
Equatorial Guinea	Brunei	China	India
Gabon	Kazakhstan	Norway	Japan
Iran	Malaysia	USA	South Korea
Iraq	Mexico		Germany
Kuwait	Oman		Spain
Libya	Philippines		Italy
Nigeria	Russia		France
Congo-Brazzaville	South Sudan		Netherlands
Saudi Arabia			
United Arab Emirates			
Venezuela			

1.2.3 Options contracts

As mentioned, petroleum and its derivatives continue to be a highly important factor for any economy and industry in the world. The previously mentioned examples of high volatility in the market for fossil fuels, possibly caused by OPEC intervention or other major political events, could have disastrous effects on enterprises that make intensive use of fossil fuels and whose profits are thus dependent on fuel costs. As a result, companies whose profits are significantly reliant on fuel costs have the incentive to reduce or counteract the business risk presented by the possibility of rising fuel costs. One prominent example is airlines, of which the majority of the airlines indeed do hedge their fuel costs to protect against future fuel price increases (Morrell & Swan, 2006). The most common method of doing so for these companies is by making use of so-called options contracts, which are derivative options contracts on an underlying asset. These contracts give the owner the right to either buy or sell the underlying asset (e.g. equity, commodities, etc.) for a given specified price on a given specified date in the future, thus protecting the contract owner against potential upward or downward price movements, depending on the owner's original exposure to the underlying asset. As such, agents that trade these contracts generally are either organizations that heavily rely on the underlying asset and attempt to hedge the risk it presents to their operations, or day traders that attempt to speculate on future asset prices.

1.2.4 Implied volatility

When investigating the global oil market, one could simply look at the running prices for oil which would potentially yield insight into how the supply and demand sides of the global oil market value the asset as is. Another possibility would be to look into how changes in the political risk situation affect the market's sentiment on the future volatility of the underlying asset. One popular way of looking at the aforementioned market volatility forecast is by making use of the so-called implied volatility, commonly referred to as IV (Mayhew, 1995). Implied volatility is a parameter commonly associated with options pricing models, such as the Black-Scholes options pricing model, and is generally understood as being the market's estimate of the underlying asset's future volatility. Conceptually, inserting this IV parameter into an options pricing model as the underlying asset's volatility, would then theoretically return an estimated options contract price equal to the current running options contract market price. As such, implied volatility is a parameter that is not directly observed, but rather calculated, and is a subjective measure of the market's expectation of future price moves of the underlying asset. Further information on how the implied volatility fits into the Black-Scholes options pricing model, will be elaborated on in the methodology section of this thesis. The implied volatility of an asset does not contain information on the direction in which the asset's price is expected to move according to the market, merely to what degree the price is expected to fluctuate. Where implied volatility is a subjective measure, historical volatility, or realized volatility is an objective measure of the underlying asset's realized price fluctuations in the past. As investors of all kinds are generally attempting to estimate and forecast an asset's future price fluctuations, they often make use of the information that is contained within an asset's historic and implied volatility to estimate the asset's future price fluctuations. Even though both of these types of volatility can be used to estimate an asset's future volatility, implied volatility is generally preferred because it is thought to contain information superior to the historical volatility, as it is supposed to be the market's estimate of the asset's future price fluctuations (Canina & Figlewski, 1993). However, the predictive power of implied volatility is not undisputed. Many papers conclude that implied volatility is a good estimator of future price fluctuations, with Shu and Zhang (2003) concluding that implied volatility is a good predictor and also is informationally superior to historical volatility. However, some papers find that implied volatility does not perform well in estimating the subsequent actual volatility of the asset (Canina & Figlewski, 1993). Likewise, Becker, Clements, and White (2007) finds that the S&P500 Implied Volatility Index (VIX) does not provide any additional information beyond the insights provided by model-based volatility forecasts. The main takeaway from the findings of these numerous papers is that neither historical nor implied volatility are perfect predictors that reliably and correctly forecast future price movements. Although implied volatility and historical volatility are not perfect predictors of future price movements, they are still commonly used by many types of investors in their investment models, especially for investing in options contracts. Since options contracts are essentially bets on an underlying asset's future price volatility, it could be very worthwhile to consider what the market's expectation of the underlying asset's future price movements is, as measured by the implied volatility. Because options are a bet on future actual volatility, when expectations for the underlying asset to fluctuate increase, the price of the options contract will increase as well as the potential value of the options contract increases, which will be coupled with an increase in the options contract's implied volatility. Even though implied volatility may not be a good ex-ante predictor of future price movements, it is still a proxy for current market uncertainty. Therefore, it could still contain valuable information on market sentiment at any point in time, as proxied by the implied volatility at that time. The consideration of implied volatility has become increasingly more important over the last two decades, as demonstrated by the popularity of the aforementioned VIX, the Chicago Board Options Exchange Market Volatility Index. This index, based on SP500 implied volatility, has now been coined the investor "fear" barometer (Whaley, 2009), as it measures investor uncertainty through implied volatility. More specifically, the VIX is an index that measures the market's volatility expectation for the coming month and is therefore often used as a predictor of market movements, and therefore has been reported by financial news outlets to an increasing degree over the past years. However, as the VIX has been gaining traction, it has been shown that VIX may also influence the international equity markets (Cheuathonghua, Padungsaksawasdi, Boonchoo, & Tongurai, 2019) through the information on market sentiment that investors extract from the VIX. Another interesting phenomenon concerning implied volatility is the existence of the so-called volatility smile. This volatility smile manifests itself when plotting the implied volatilities of multiple options contracts, with the same underlying asset and maturity, but different strike prices. The resulting graph generally resembles a smile, with the lowest point of the graph coinciding with options contracts with a strike price that is at-the-money (ATM) or very close to ATM. As the strike price moves away from the underlying asset's price, i.e. it moves away from being ATM, and thus becomes increasingly in-the-money (ITM) or out-of-the-money (OTM), it is generally observed that the implied volatility of these contracts is gradually increasing more and more, thus giving rise to the convex shape of the implied volatility graph and the shape of a smile. This peculiar relationship between the distance of the strike price from the underlying asset's price and the volatilities implied by an options contract's price has not always been observed in the options markets. Specifically, it has been observed that these volatility smiles started appearing in equity options markets after the 1987 Black Monday stock market crash (Hull, 2003). This rather sudden change in dynamics is generally explained as being caused by options traders realizing that they would need to price in extreme events, as demonstrated by the 1987 stock market crash. Consequently, options traders would increase their prices for options that are deep ITM or OTM, thus also resulting in higher implied volatilities for these options contracts. The existence of the volatility smile also has consequences for the validity and accuracy of options pricing models. The consequences become clear when analyzing the gap between the Black-Scholes calculated implied volatilities and the actual observed implied volatilities in the options markets, as the implied volatilities calculated with the Black-Scholes options pricing model were much closer to the actual observed implied volatilities in the options markets before the volatility smiles were observed. Under the Black-Scholes options pricing model and its assumptions, the observed implied volatility should be constant for options contracts on the same underlying asset and with equal maturity, even when these options contracts have different strike prices (Pena, Rubio, & Serna, 1999). It is now observed that the Black-Scholes options pricing model is less accurate at predicting prices for deep ITM and OTM options, which is due to the observed volatility smile. However, the Black-Scholes options pricing model's accuracy should not be significantly impaired by the volatility smile in pricing options contracts that are ATM or close to it. To conclude, it could be very insightful to look into the market uncertainty and how it reacts to fluctuations in certain other variables. As stated, one common way to investigate market uncertainty is by using implied volatility as a proxy for market uncertainty. Since volatility is also a very important factor for options pricing, it can be very insightful to research the connection between oil options contracts' price implied volatility and political risk as an influence on this implied volatility (Xiao, Hu, Ouyang, & Wen, 2019). Looking at market uncertainty can be both practically and empirically worthwhile. Firstly, insight into how market uncertainty reacts to certain changes in the global economy can be practically interesting, since market uncertainty has been a factor that influences investors of all kinds through many mechanisms. As an example, Chiang, Li, and Yang (2015) finds support for the hypothesis that stock-bond return correlations are influenced by financial market uncertainty, and likewise, Sarwar and Khan (2017) finds that fluctuations in the earlier mentioned VIX are associated with changes in emerging market returns. As such, understanding the factors that influence market uncertainty, and in turn the relationship between market uncertainty and other financial market outcomes (such as returns) can be very interesting to any kind of investor. Moreover, adding to the existing academic literature on factors that may influence market uncertainty would be academically worthwhile, as it adds to our understanding of how the financial markets function and react to changes in the global economy.

1.2.5 Liquidity, trading volume and open interest

Another important factor to consider in the context of financial markets is the concept of liquidity and trading volumes. Liquidity can be seen as the ease with which an asset can be sold or bought on a market with as little compromise in the selling and buying price of the asset. In the situation of a highly liquid market (as is the case with most stocks, bonds and ETFs), financial agents can rapidly buy and sell goods and not have to compromise on the buying or selling price of the good to facilitate the occurrence of the trade. On the other hand, in illiquid markets (such as real estate, or highly specific assets) financial agents may have more trouble when they want to buy or sell an asset quickly, as there are simply fewer other agents in the market that are looking to buy or sell the asset, which means that the agent may have to compromise on the buying or selling price of the asset or will have to wait with the desired transaction. As mentioned, the price of the goods that are being exchanged is determined by how these two sides interact with each other through the law of demand and supply and also changes as a result of changing dynamics between these two sides. In this situation, it is also important to consider how many exchanges are taking place. This is referred to as the trading volume, or the number of exchanges taking place in a specific market, i.e. the total number of trades taking place in a specific asset within a specified time window, which is often used to assess the trading activity in a given asset in securities markets and is a representation of the market's liquidity. Trading volume has been shown to be a determinant of volatility within many types of markets (Chen, Firth, & Rui, 2001; Brailsford, 1996; Bessembinder & Seguin, 1993; Bollerslev & Jubinski, 1999) and has therefore been proven to be an important factor to consider within markets. Generally, the activity within a market is referred to as the aforementioned trading volume in that specific market.

However, in the case of futures and options contracts, one can imagine that the degree of activity can also be captured by the number of outstanding contracts that are yet to be closed out, which is referred to as the open interest on a given contract. The open interest of a contract directly influences the given market's dynamics, as a large open interest (i.e. a large number of outstanding contracts), means that there is a large number of buyers and sellers in the market for that given securities' options contract and thus contains information on the degree of activity within a market. Intuitively, Ripple and Moosa (2009) have indeed found that the open interest on an options contract influences volatility in crude oil futures contracts, and could therefore help in explaining variation in the dependent variable of the analyses in this paper. Additionally, (Næs, Skjeltorp, & Ødegaard, 2011) finds that liquidity in the financial markets is also closely related to the evolution of the business cycle. Therefore, including liquidity in the analysis would also introduce information on the real economy business cycles into the analysis.

1.3 How country and political risk influence financial markets

Combining the subjects of the two main subsections of this section produces a hypothetical relationship between country / political risk factors and the financial markets and their dynamics, such as asset prices and market uncertainty. Some literature already exists on this relationship. For instance, (Goodell & Vähämaa, 2013) finds that the previously discussed VIX tends to increase as the outcome of the United States presidential election becomes more certain, thus showcasing a negative relationship between investor uncertainty in stock markets and the political uncertainty regarding the election. This reinforces the notion of the impact that political factors can have on financial markets. Additionally, (Białkowski, Gottschalk, & Wisniewski, 2008) find that the occurrence of elections on a national level in OECD countries is associated with a large increase in the country-specific component of index return variance. Delving more into the nature of the relationship between country and political risk factors and financial markets, (Andrianaivo & Yartey, 2010) shows that country and political risk factors influence the development of financial markets, further exposing the connection between the former and the latter. Further elaborating on the evidence in the United States, (Santa-Clara & Valkanov, 2003) finds that returns in the stock market differ across Democratic and Republican presidencies which can not be justified by other potential causes, such as business-cycle variables, thus adding to the evidence that the political climate could have an impact on financial markets. Smales (2015) investigated the relationship between political uncertainty (which thus inherently imposes political risk) and financial market uncertainty in Australia and finds a positive relationship between the two. Similarly, Beaulieu, Cosset, and Essaddam (2006) finds that the stock returns of firms based in Quebec, Canada, were influenced by a referendum held in the city of Quebec. (Kaminsky

& Schmukler, 2002) investigates the relationship between sovereign debt ratings, country risk and financial markets, and finds that sovereign debt ratings (which could also be considered a proxy for country risk) have effects beyond the scope of debt, but also in stock markets. This is an example of how country risk factors could have a significant effect on financial markets. As a final remark, one should also note the intervening role of national governments in the financial markets. Throughout modern history, we have seen several examples of the political climate having an effect on financial markets through the mechanism of government intervention. In his paper, (Stiglitz, 1993) provides us with a broad taxonomy of these types of government interventions, which have often occurred in response to some form of a perceived market failure in the financial markets. The existence and occurrence of this type of government intervention is yet another form of connection between political factors and the financial markets and further strengthens the hypothesized relationship between country and political risk factors and the financial markets. Concluding, the existing literature has already investigated some instances where there seems to be a relationship between country and political risk and uncertainty in the financial markets. However, these previous inquiries into this relationship between country and political risk and uncertainty in financial markets have often been done in the context of a significant political event taking place in a short period of time. The research in this paper will differentiate itself from this set of research by also focusing on long-term changes in the country and political risk environment, thus potentially also including gradual changes in country and political risk.

1.4 Hypothesis

Combining all the concepts mentioned in this section leaves us with the question of how and if these concepts are related to each other. Therefore, in this paper, I will be investigating the hypothesized relationship between country and political risk in oil exporting countries and the implied volatility captured within crude oil options contract prices. Insights gained from investigating this hypothesis will then add to the understanding of how changes in the country and political environment in oil exporting countries affect the global oil market. Therefore, the two main hypotheses of this paper will be as discussed below.

As discussed previously, shocks in the form of country-specific (political) events can have great consequences for the dynamics of the global crude oil market, and thus the running price of crude oil. Therefore, the first hypothesis of this paper relates to the hypothesized effect between country and political risk in countries that are important to the global crude oil market and the running price for crude oil in global markets:

H1: The political risk or country risk in countries that are relevant to the global oil market have an effect on the running price for crude oil in crude oil markets.

The second hypothesis of this paper relates to country and political risk in countries that are important to the global crude oil market and the potential effect that shocks in the form of country-specific (political) events could hypothetically have on the market uncertainty within the global crude oil market, as measured by the options contract price implied volatility:

H2: The political risk or country risk in countries that are relevant to the global oil market have an effect on the market uncertainty in crude oil options contract markets as measured by the implied volatility.

The next section of this paper will elaborate on the data that will be used to investigate the aforementioned hypothesis.

2 Data

2.1 Crude oil options

In this thesis, I will be investigating the effects of country and political risk on crude oil prices and the crude oil options contract price implied volatility. Therefore, the first set of data I will be using in my analysis is daily data on the dependent variables of my analysis, namely the daily running price of crude oil and the crude oil options contract price implied volatility. For my analysis, I have opted to look at a continuous series of light, sweet crude oil options contracts at 100% moneyness, which is retrieved from Eikon Datastream. This set of data includes a time series of the price of the underlying asset (crude oil) and also the implied volatility in percentages as implied by the option prices for multiple times to maturity, namely 1, 2, 3, 6, and 9 months and 1, 2, 3, 4 and 5 years to maturity. The implied volatility in this data set has been calculated with the use of the so-called Generalized Black-Scholes (GBS) model for commodity option pricing, which will be expanded upon in section 3. Additionally, the data set contains data on the open interest and trading volumes in the options contracts for the aforementioned maturities. I will then sum the open interest and trading volumes for all the maturities to come to a daily open interest and trading volume time series, as the previously mentioned continuous series also includes options contracts of all maturities. The descriptive statistics for the variables on open interest and trading volume are listed in table 2.

Table 2: Descriptive statistics on open interest and trading volume

Variable	Observations	Mean	St. Dev.	Min.	Max.
Open interest	121	13130.812	11909.645	1145.481	108024.05
Trading volume	121	1349.287	810.446	173.935	4104.461

The aforementioned set of data that is retrieved from Eikon Datastream from the at-the-money light, sweet crude oil options contracts continuous series is an artificial series that is calculated and produced by the Eikon Datastream platform. This series has been calculated by making use of options contracts with strike prices that are very near the money (NTM), which are then aggregated as weighted by their distance from being at-the-money. By doing so, an artificial series is construed for what would be an at-the-money options contract. Additionally, these continuous series are being calculated by using a basket of multiple options contracts, meaning that the maturities of these individual options contracts can be "rolled over", resulting in an options contract series that does not expire until the underlying type of options contracts does not exist anymore. This represents a major benefit over individual options contracts, as the continuity of the continuous series means that they have much more history available. The calculation of the implied volatility for the oil options contracts is also part of this continuous series of data. The implied volatility at a certain date is calculated by making use of the options contract with the nearest maturity. After this contract goes to maturity, the continuous series rolls over to the options contract with the next nearest maturity. This process is then repeated automatically until the present day, or until the underlying options contract does not exist anymore.

2.2 Country and Political risk data

2.2.1 Monthly country risk data from Refinitiv

The data on the explanatory variable in my analysis, pertaining to the country risk of individual countries, will be retrieved from the Refinitiv Country Risk Ranking database. This database contains data on the individual country risk levels of most countries in the world and combines the different sources of country risk into one comprehensive measure that is updated monthly. The data on the different sources of country risk is sourced from over 300 public domain sources from third parties, such as the World Bank, the European Union, the United Nations, and the Organisation for Economic Co-operation and Development (*Refinitiv Country Risk Ranking*, 2022). The data from these external sources include several risk factors that are divided into three main risk dimensions, namely political, economic, and criminal. The political risk dimension is mostly concerned with how the national government functions in the focal country and includes measures that assess the performance of the government, but also other factors of the national political climate. Examples of such risk factors that are included in this risk dimension are the type of governance, civil liberties & political rights, political stability. However, other risk factors, such as government effectiveness & opacity, and regulatory quality are also included. Furthermore, this risk dimension also includes factors that are concerned with the risk of major political events occurring that are relevant to the stability of the political environment in a country, such as the degree of political terror, risk and occurrence of armed conflict. The economic risk dimension is predominantly concerned with assessing a country's business environment and factors that concern the economic performance of a country. For example, risk factors that are included in this risk dimension are the country's GDP per capita, existence of natural resources, poverty, debt, military expenditures, sovereign credit ratings and economic freedom. Additionally, this risk dimension also considers risk factors that lie on the fringe of the political and economic risk dimensions, namely sanctions by other countries or economic entities which are often politically motivated but generally have economic consequences for the country affected by them. The third risk dimension is concerned with risk pertaining to criminal activity within the focal country and contains risk factors that relate mainly to criminal activity within the country but are often also related to one or both of the other risk dimensions. Risk factors that are included in the criminal risk dimension are the degree of fraud & embezzlements, crime rates, corruption, exploitative labor, threat financing, and illicit drugs & narcotics. Intuitively, the aforementioned risk factors are often not only associated with their main risk dimension, but also with another, or even all of the three risk dimensions. For example, criminal risk factors (such as fraud & embezzlements, crime rates, and corruption) are often closely related to the political risk dimension, as these can also be a consequence of the (lacking) political environment in place (Scheingold, 1995). Additionally, one can imagine that economic factors such as military expenditures are also closely related to the political risk dimension through political risk factors such as the likelihood of armed conflicts occurring (Smith, 1989). Because of this tight relationship between these three risk dimensions, it is definitely interesting to jointly consider all these dimensions in this paper's analysis on the effects of country risk on global crude oil markets. The data from these external sources is then aggregated and condensed into 3 types of weighted risk rankings, namely Anti Money Laundering, Anti Corruption, and Comprehensive. The first two of these are mostly aimed towards servicing businesses in the financial services sector, as part of their customer due diligence and risk management processes, assisting in Know Your Customer processes and assessing the location-based risk of operations (which only very recently have been recognized as essential risk assessment processes). To this end, the risk weighting under the Anti Money Laundering and Anti Corruption risk rankings is specifically tailored to accommodate the needs of financial service providers that attempt to get insight into either Anti Money Laundering related risk or Anti Corruption related risk. The Comprehensive weighted risk ranking, on the other hand, considers all the risk factors without favoring some factors over others in the weighting of the risk ranking. For my analysis, I have retrieved monthly data from this data source ranging from the year 2012 through 2022 on a number of countries. These countries include current OPEC members, members of the OPEC+ group (an alliance that includes countries that are not members of the original OPEC), and other countries that play significant roles in the oil market through their export or import numbers. The list of the 36 countries included in these subsets can be seen in table 1. This data set assigns each country a monthly score, ranging from 0 to 10, with 10 representing the lowest degree of country risk and thus the most stable countries, and 0 representing the highest degree of country risk and thus the most unstable countries. It should be noted that this country risk score (CRS) is not scored on a linear scale. This means that a CRS of 1.0 is not 2 times as risky on a country risk level as a country with a CRS of 2.0, and thus means that a jump from a CRS of 2.0 to 1.0 denotes a much larger increase in country risk than a jump from 5.0 to 4.0. This type of data does allow parametric testing, but it should be noted that this does have implications for the interpretation of any results the analysis on this data set yields. Looking closer at this set of data provides us with descriptive statistics as shown in table 3.

Table 3: Descriptive statistics on monthly country risk scores for all countries

Variable	Observations	Mean	St. Dev.	Min.	Max.
Algeria	120	2.093	.296	1.47	2.65
Angola	120	2.301	.445	1.47	2.97
Azerbaijan	120	2.944	.695	1.52	4.52
Bahrain	120	3.1	.642	1.96	4.22
Brazil	120	4.875	.713	4.08	6.38
Brunei	120	8.29	.31	7.81	8.78
Canada	120	8.296	.645	7.49	9.31
China	120	4.172	.491	3.09	5.06
Congo Brazzaville	120	2.094	.536	1.00	2.88
Equatorial Guinea	120	4.506	.373	3.95	5.67
Gabon	120	3.969	.475	3.35	4.9
Iran	120	1.641	.949	.53	3.56
Iraq	120	.456	.133	.23	.62
Kazakhstan	120	5.608	.316	5.22	6.48
Kuwait	120	6.715	.465	6.21	7.39
Libya	120	1.707	1.932	.23	6.59
Malaysia	120	6.746	1.092	4.42	8.12
Mexico	120	3.015	.958	1.9	4.51
Nigeria	120	.92	.322	.37	1.39
Norway	120	8.356	.698	7.49	9.34
Oman	120	7.264	.23	6.93	7.73
Philippines	120	2.639	.586	1.49	3.63
Russia	120	2.47	.354	1.54	3.14
Saudi Arabia	120	4.179	1.176	2.88	6.19
South Sudan	120	.456	.231	.14	.94
United Arab Emirates	120	7.051	1.143	5.05	8.2
United States	120	4.146	1.864	1.69	7.06
Venezuela	120	1.229	.121	1.05	1.74
Japan	120	8.654	.409	7.97	9.19
France	120	7.767	.56	6.59	8.47
Spain	120	7.726	.725	5.79	8.66
Germany	120	8.569	.481	7.62	8.96
Netherlands	120	8.719	.402	7.95	9.06
Italy	120	7.86	.601	6.41	8.59
India	120	3.606	.482	2.51	4.22
South Korea	120	6.51	.699	5.03	7.68

Here we can see that included in this data set are 120 observations for each of the 36 included countries' CRSs, with a monthly observation for every year in the 2012-2022 time period starting in August of 2012 and reaching until August 2022. This adds up to a total of 4,320 observations of countries' CRSs. Additionally, we can see that the countries the Netherlands, Japan and Germany report the highest mean CRSs (8.719, 8.654 and 8.569 respectively), which translates to them, on average, being the countries with the least country risk in that regard. On the other hand, the countries Iraq, South Sudan, and Nigeria report the lowest mean CRSs (0.5, 0.5 and 0.9 respectively), meaning that these countries, on average, are subject to the highest degree of country risk. Here, it is interesting to note that the three countries that are on average subjected to the lowest degree of country risk, are all countries that are included in the subcategory of oil importers, whereas the three countries with on average the highest degree of country risk are all part of one of the subcategories of oil exporters. This notion can be reconciled by the fact that the biggest oil importers are generally large economies with high crude oil requirements, but which are not endowed with sufficient crude oil resources to sustain their economies' requirements. This condition happens to mostly coincide with the Western world and some large Asian economies. As a result, all of the countries included in the oil importers subcategory are either located in the Western world or the more economically developed parts of Asia. On the contrary, oil-producing countries are generally located outside the Western world, and are often found in Africa, the Middle East or South America, of which the countries are generally less economically developed than their counterparts in the Western world. As a result, these countries are generally subject to more turbulent economic and political environments. As such, it is not surprising that the three countries with the, on average, highest degree of country risk are all located in the Middle East and Africa, with many of the other countries with high degrees of country risk in the sample also being located in these regions or in South-America. It is also interesting to note that Libya is the country with the highest standard deviation in CRS, namely 1.932. Looking at the data, it becomes apparent that this large degree of CRS fluctuation takes place in the last months of the year 2012. Where Libya scored 6.6 in August 2012, this score quickly dwindled to 4.8 in October 2012, then to 3.1 in March 2015, and eventually to 0.6 in October 2015 after which it continued to decrease steadily towards a score of 0.3 in August 2022. This evolution of the CRS suggests a disastrous unwinding of the business environment in Libya, and this can of course be reconciled with the Libyan crisis, which started in 2011 with the outbreak of the Arab Spring. Since then, the Libyan crisis has seen multiple civil wars destabilizing the country, thus explaining Libya's poor CRSs. The country with the second highest standard deviation is the United States, with a standard deviation of 1.864. Looking at the data, it becomes clear that there are several big jumps in the US's CRS which could explain this high degree of standard deviation. Firstly, near the end of 2012, the CRS increased from 6.0

to 7.0, which then decreased to 5.9 in March 2015, moving to 3.7 at the end of 2015, then decreasing to 2.2 in March 2020, and steadily decreasing to 1.8 in August 2022. Arguably the most important event for the business climate in the US, are the presidential elections which are held in the month of November at 4-year intervals. At least one of the big CRS changes mentioned previously coincide with the occurrence of these presidential elections (such as the 2012 score increase and Obama's win) and could therefore potentially be explained by them. The striking decrease in CRS near the end of 2015 coincides with the Islamic State militant group coming to the fore in the Middle East, launching terrorist attacks globally and expanding its influence in the region or Iraq. The United States, together with a coalition of other countries launched Operation Inherent Resolve, including military intervention against the Islamic State. This (globally) tumultuous time period could be a potential explanation for the CRS decrease near the end of 2015. The country with the third highest standard deviation in CRS is Saudi Arabia, with a standard deviation of 1.176. Looking closer into the monthly CRSs for Saudi Arabia reveals that the country has experienced some very significant jumps in its CRS. Firstly, the country has moved from a CRS of 3.4 in March of 2015, to a score of 6.19 in October of 2015. This large positive move, translating to a decrease in the degree of country risk, happens to coincide with an eventful time period for Saudi Arabia as a country, as 2015 saw a change in head of state where King Salman was named king after the death of his predecessor, Abdullah bin Abdulaziz in January 2015. Additionally, in April 2015, King Salman appointed his nephew, Muhammad bin Nayef as the new Crown Prince of Saudi Arabia [2]. As a great deal of the Kings discretion resides de facto within the hands of the Crown Prince in Saudi Arabia, this constituted a major change in the nation's government, and could thus be used to explain the major fluctuation in Saudi Arabia's CRS in that specific time period. After this huge increase in CRS, the score remained stable until March 2018. Then, Saudi Arabia experienced another large fluctuation in its CRS, as it dwindled from 6.01 in April 2018 to 3.05 in March 2020. This large negative move in CRS, translating to an increase in country risk, takes place in a year where the Saudi Royal Family came under fire for allegedly ordering the killing of dissident Saudi Journalist Jamal Ahmad Khashoggi, which was met with a global public outcry and scrutiny on the Saudi Royal Family (Rashad & Hosenball, 2019). After this, the CRS remained largely stable until August 2022.

After transforming the data to a panel format to allow for within- and between-countries CRS analysis of standard deviations, descriptive statistics for this set of data were retrieved.

[2] The tenure of Muhammad bin Nayef was relatively short-lived as he was replaced in 2017 by current Crown Prince Mohammad bin Salman

These descriptive statistics are shown in table 4. Here, we can see that there are in total 4,320 observations of CRSs, spread out over 36 countries with 120 observations each on the same dates ranging from August 2012 to August 2022. Looking at the between- and within-country standard deviation, we can see that the within-country standard deviation of .742 is much smaller than the between-country standard deviation of 2.722. This is to be expected, as the countries within the used data are quite different in economic, political and cultural aspects. Additionally, it is highly unlikely that a country's risk score spontaneously moves from one to the other side of the spectrum of risk scores, as country risk is generally a result of many processes that do not occur instantaneously, but rather develop slowly. Comparing the mean CRSs for some countries may reveal some pairs of countries with surprising differences. Example given, the United States reports a mean CRS of 4.146, which is well below the mean CRSs of any of the other countries belonging to the economic west. This is partly caused by the fact that country risk conceptually consists of the probability of sudden and unforeseen changes occurring in a national context, as discussed in section 1. Additionally, the data on CRSs have been produced through a specific methodology of calculating a comprehensive CRS, and any results yielded by the analysis of this data set are thus subject to this specific CRS methodology.

Table 4: Between and within descriptive statistics on monthly country risk score

Variable	Mean	St. Dev.	Min.	Max.	Observations
Risk score	4.740	2.785	.14	9.340	N = 4,320
Between		2.722	.456	8.711	n = 36
Within		.742	2.284	9.623	T-bar = 120

2.2.2 Annual political risk data from Oxford Economics

In order to augment the strength of my analyses, another source of data on political risk will also be considered, namely data from the Oxford Economics annual Economic and Political Risk Evaluator, or EPRE in short (*Oxford Economics Economic and Political Risk Evaluator*, n.d.). This data source includes data on economic and political factors in over 200 countries. Like the previously discussed risk data source from Refinitiv, this data source is similarly used by parties to assess risks of all sorts affecting their operations. The EPRE, as suggested by the name, contains data points that are relevant to the economic and political risk situations in each country covered. These data points are generated by aggregating political event analyses from a network of Oxford Economics' partners, which are aimed at measuring and monitoring the consequences of political issues. The data points that are included in the calculation of the risk score can then be individually weighted to specifically suit the risks that the user wants to assess.

For this paper's analysis, I have opted to use the Political Stability risk score weighting in order to retrieve data that is representative of each country's political risk situation. This risk weighting in the Oxford Economics EPRE is aimed at assessing the stability of the current government and the overall political system (*Oxford Economics Economic and Political Risk Evaluator*, n.d.). This weighting thus is a measure of political risk as defined in the introduction, as political risk is measured by the degree of unforeseeable changes in the political environment, which can also be described as the absence of political stability and would thus translate to a political risk score indicating low political stability.

A set of data has been retrieved from this source, containing data on the political risk scores of the 36 focal countries of this paper ranging from the year 2012 - 2022. These annual political risk scores per individual country range from 0 to 10, with 0 representing the most stable countries with regard to political risk, and 10 representing the most unstable countries. This set of data consists of 393 observations of the political risk score for the 36 aforementioned countries, with 11 observations ranging from 2012-2022 for all but one country. The one exception is South Sudan, which has only been covered since 2015 and as a result, has 3 observations less than the other countries. However, since this source of data is annual, the time period of 2012-2022 results in only 11 annual observations of political risk scores per country. Therefore, performing statistical analyses on this data set is unlikely to be worthwhile, as the number of observations is simply too low to produce any statistically significant results. However, this smaller data set will be used to check the consistency of the findings of the main analysis involving the monthly CRSs, as described in the previous section. Additionally, even though this set of data is not suitable for statistical analyses, I will perform a qualitative analysis of the data to gain closer insights into how risk score methodology works in general and how these risk scores react to their respective environments. As was the case for the country risk data set, the data on political risk scoring also follows a non-linear scale. The descriptive statistics for this data set are shown in table **??**.

Table 5: Descriptive statistics on annual political risk scores for all countries

Country	Observations	Mean	St. Dev.	Min.	Max.
Algeria	11	6.136	.067	6	6.2
Angola	11	5.418	.632	4.7	6.2
Azerbaijan	11	6.245	.25	6.1	6.9
Bahrain	11	3.9	0	3.9	3.9
Brazil	11	5.482	.194	5	5.7
Brunei	11	1.909	.151	1.8	2.2
Canada	11	2.564	.737	1.8	3.6
China	11	5.118	.289	4.8	5.6
Congo Brazzaville	11	8.327	.335	7.5	8.7
Equatorial Guinea	11	4.764	.092	4.6	4.9
Gabon	11	5.636	.163	5.4	5.8
Iran	11	7.227	.215	6.9	7.6
Iraq	11	7.455	.234	7.2	8
Kazakhstan	11	5.536	.401	4.9	6
Kuwait	11	4.164	.143	4	4.3
Libya	11	9.509	.305	9.2	10
Malaysia	11	3.991	.226	3.7	4.5
Mexico	11	5.145	.434	4.4	5.7
Nigeria	11	7.309	.114	7.2	7.5
Norway	11	2.309	.192	2	2.6
Oman	11	3.136	.18	2.9	3.5
Philippines	11	4.5	.1	4.4	4.6
Russia	11	6.127	.179	5.9	6.5
Saudi Arabia	11	5.364	.092	5.2	5.5
South Sudan	8	8.413	.099	8.3	8.5
United Arab Emirates	11	2.691	.202	2.6	3.1
United States	11	3.191	1.065	2	4.5
Venezuela	11	8.191	.351	7.8	8.6
Italy	11	3.009	.418	2.3	3.5
France	11	3.191	.416	2.6	3.7
Netherlands	11	2.536	.136	2.4	2.7
Japan	11	2.945	.181	2.7	3.3
India	11	6.391	.212	6.1	6.7
Germany	11	3.2	1.71	1.9	7.3
Spain	11	3.618	.125	3.5	3.8
South Korea	11	3.564	.225	3.2	3.8

In this table, we can see the mean, standard deviation, minimum, and maximum for each of the 36 included countries. Here we can see that Brunei, Norway, and the Netherlands are the three countries with the lowest mean political risk score (respectively 1.909, 2.309, and 2.536), meaning that, on average, these countries were subject to the lowest degree of political risk. On the other hand, Libya, South Sudan and Congo-Brazzaville were the countries with the highest mean political risk score (respectively 9.509, 8.413 and 8.327), meaning that, on average, these three countries were subject to the highest degree of political risk. Visual inspection of the series of countries' political risk scores shows that most of the series are rather static with only minor and few deviations from the mean political risk scores. Looking at the countries' standard deviation in political risk scores shows that Germany, the United States of America and Canada are the countries with the largest standard deviation in terms of political risk score (respectively 1.71, 1.065 and .737). It might be quite surprising that Germany, a country generally thought to be relatively stable in economic and political terms, is the country with the highest standard deviation in its political risk score in the sample. When looking at the data, it becomes apparent that this standard deviation is mostly caused by a large jump in political risk score in the years 2012-2014. In 2012, Germany had a political risk score of 5.8, which moved to 7.3 in 2013 and afterward back to 2.1 in 2014. This large jump could be explained by a major political event that occurred in 2012. After a large scandal in January 2012 surrounding the incumbent President Christian Wulff concerning his connections to influential German businessmen and his alleged attempt to cover it up (CNN, 2012), Wulff resigned as president of Germany. Subsequently, a presidential election was hosted, after which Joachim Gauck was named successor of Christian Wulff as German President. While this may be used as an explanation for the fluctuation in Germany's political risk score, it should be noted that the role of the German President is mostly a ceremonial one, meaning that there may be other factors at play causing the political risk score fluctuation.

The United States of America displays one of the largest movements in political risk score in the data set between the years 2016 and 2017, moving from 2.3 to 3.7, which constitutes a deterioration in terms of political risk. As mentioned previously, this large fluctuation in political risk could very well be explained by the 2016 presidential elections. This election saw Republican presidential nominee Donald Trump being elected as president of the United States of America and was controversial in many regards. For example, Trump lost the popular vote by 2.8 million votes but won through the electoral college, giving him the presidency (*United States Presidential Election of 2016.*, n.d.). On top of that, there were allegations that Russia had attempted to interfere with the elections (*Factbox: Key findings from Senate inquiry into Russian interference in 2016 U.S. election*, n.d.). Additionally, Trump's presidential campaign was full of controversial and populist ideas and standpoints, of which the potential consequences caused some (political) unrest after his win. These factors could explain the large fluctuation in the USA's political risk score between 2016 and 2017.

Canada also saw a big fluctuation in political risk scores between the years 2016 and 2017, deteriorating from 2.0 to 2.8. Closer inspection reveals no big changes in terms of the Canadian political environment, however, the deteriorated political risk situation may have been caused by the changing political situation in the USA, with which Canada holds a very important and sizable economic relationship. To demonstrate, Canada and the USA are engaged in one of the largest (bilateral) trade relationships in the world, which in 2021 consisted of over 1 trillion USD in goods and services, and resulted in Canada being the largest trade partner of the USA. As previously discussed, the 2016 presidential elections in the USA might have been the catalyst for the deteriorating political risk situation in the USA. Due to the reliance on each other in their bilateral trade relationship, the political situation in the USA could well affect Canada's political situation as well. This could be a possible explanation for the deterioration of Canada's political risk score at the same time as the USA's political risk score.

Next, after transforming the data to a panel format, we can take a closer look at how the political risk scores behave within and between the 36 included countries. The panel descriptive statistics on the data set of annual political risk scores are shown in table 6. Here, we can see that the overall standard deviation in the annual political risk score is 1.999, which is lower than the 2.785 standard deviations found in the monthly CRS data set. This large difference could be a result of inherent differences between the calculation of both risk scores, but a more likely explanation is that this difference is caused by the different aggregation levels for the monthly CRSs and the annual political risk scores. As the risk score series for a country are generally stable in the long run, annual risk scores could "remove" fluctuations that would be included in monthly risk scores, which could then lead to a lower standard deviation on the annual level as compared to the monthly level. Furthermore, we can see that the within-country standard deviation is much lower than the between-country standard deviation, respectively being 0.416 and 1.997, as was also the case for the monthly CRSs.

Table 6: Between and within descriptive statistics on annual political risk score

Variable	Mean	St. Dev.	Min.	Max.	Observations
Risk score	4.924	1.999	1.8	10	N = 393
Between		1.997	1.909	9.509	n = 36
Within		.416	3.624	9.024	T-bar = 10.917

Further comparison of the country and political risk score data provides the information in table 7. In this table, we can see a comparison of the countries' mean risk scores and subsequent risk rankings under the separate country and political risk score methodologies. In the 5th column, the absolute difference in rank under the two risk score methodologies is presented. When this column reports a value of 0, then both risk score methodologies have assigned that specific country with the same risk score rank within the sample. Looking closer at this column shows that, in general, the two different risk score methodologies assign quite similar ranks to the 36 included countries. However, it does seem that the two risk score methodologies are more in consensus with each other for the countries that are subject to either the lowest or the highest degrees of risk. This is evident by the fact that the rank differences are relatively low with few extremes on either end of the distribution, while the middle of the distribution has some high rank differences between the two risk score methodologies.

Table 7: Comparison of relative country risk score and political risk score ranking

Country	Mean CRS*	CRS rank	Mean PRS**	PRS rank	Rank diff.***
Netherlands	8.719	1	2.536	3	2
Japan	8.654	2	2.945	6	4
Germany	8.569	3	3.2	11	8
Norway	8.356	4	2.309	2	2
Canada	8.296	5	2.564	4	1
Brunei	8.29	6	1.909	1	5
Italy	7.86	7	3.009	7	0
France	7.767	8	3.191	9	1
Spain	7.726	9	3.618	13	4
Oman	7.264	10	3.136	8	2
United Arab Emirates	7.051	11	2.691	5	6
Malaysia	6.746	12	3.991	15	3
Kuwait	6.715	13	4.164	16	3
South Korea	6.51	14	3.564	12	2
Kazakhstan	5.608	15	5.536	24	9
Brazil	4.875	16	5.482	23	7
Equatorial Guinea	4.506	17	4.764	18	1
Saudi Arabia	4.179	18	5.364	21	3
China	4.172	19	5.118	19	0
United States	4.146	20	3.191	10	10
Gabon	3.969	21	5.636	25	4
India	3.606	22	6.391	29	7
Bahrain	3.1	23	3.9	14	9
Mexico	3.015	24	5.145	20	4
Azerbaijan	2.944	25	6.245	28	3
Philippines	2.639	26	4.5	17	9
Russia	2.47	27	6.127	26	1
Angola	2.301	28	5.418	22	6
Congo Brazzaville	2.094	29	8.327	34	5
Algeria	2.093	30	6.136	27	3
Libya	1.707	31	9.509	36	5
Iran	1.641	32	7.227	30	2
Venezuela	1.229	33	9.191	33	0
Nigeria	.92	34	7.309	31	3
Iraq	.456	35	7.455	32	3
South Sudan	.456	36	8.413	35	1

**For the country risk score, higher scores mean a lower degree of country risk*
***For the political risk score, higher scores mean a higher degree of political risk*
****Absolute rank differences between the country risk rank and political risk rank*

2.2.3 Country oil export and import data

In order to calculate the weighted average political scores by relative oil production numbers for the given subsets of countries, I will retrieve annual crude oil production numbers from the site of the U.S. Energy Information Administration (EIA). This set of data contains annual crude oil production numbers in millions of barrels per day (Mb/D) on all of the countries mentioned in table 1 in the time period between 2012 and 2021. Since the annual data on oil production was not yet available for the entire year 2022, I will use the countries' oil production values from the year 2021 to calculate the weighting for the OPEC political risk score. Similarly, for the "Importers" subcategory of countries, I will retrieve data on these countries' oil import data during the years 2012-2022 from the EIA. The data retrieved from the EIA on these 10 countries contains the annual crude oil imports in Mb/D over the aforementioned time period. However, the data on the oil imports per country was not complete for the entire 2012-2022 time period, as there was only recorded data until the year 2020. Additionally, the countries China and India did not have recorded data for the years 2019 and 2020. In order to come to a complete risk weighting methodology (despite the missing import data for some countries and some years) I have opted to extrapolate the import data of that specific country's last recorded year to the missing years, which means that the split in risk score weighting by annual oil imports is constant for the years 2020, 2021 and 2022. Additionally, the oil import numbers used for China and India are constant over the years 2018, 2019, 2020, 2021 and 2022, where the year 2018 is the last year where actual oil import data has been recorded for these two countries.

2.3 Crude oil prices

As mentioned, a data set containing daily crude oil prices has been retrieved. However, in order to merge this set of daily data with the monthly data on risk scores, I will calculate the monthly average crude oil price and combine these sets of data. Descriptive statistics on the crude oil prices are shown in table 8. In that table, we can see that the price of crude oil in the data set has moved between a minimum of 17.05 and 114.26 US dollars per barrel of crude oil. The minimum of 17.05 US dollars per barrel of crude oil was achieved in the month of April 2020 and the maximum of 114.26 US dollars per barrel of crude oil was achieved in the month June of 2022.

Table 8: Descriptive statistics on crude oil price

Variable	Observations	Mean	St. Dev.	Min.	Max.
Price	121	66.279	22.719	17.045	114.26

2.4 Crude oil options contract price implied volatility

The data on the crude oil options contracts' price implied volatilities are shown in table 9 for all of the included time periods, ranging from 1 month implied volatility to the 5 year implied volatility. Here we can see that across the different time periods, the mean implied volatilities are decreasing as the time period increases in length. However, there is one exception to this, as the 5 year mean implied volatility is slightly higher than the 4 year mean implied volatility. Further inspection reveals that the smallest value for implied volatility occurred in the 5 year implied volatility, with an implied volatility of 13.0%. Conversely, the largest value for implied volatility occurred in the 1 month implied volatility with a value of 243.6%. Additionally, it is interesting to note that the standard deviation across the implied volatility over the different time periods is decreasing as the time periods increase in length up until the 3 year implied volatility, where the standard deviation of the implied volatility is equal to .055 or 5.5%. Then, the standard deviation across the different implied volatilities increases over the 4 year and 5 year implied volatilities, with a standard deviation of .097 and .177 respectively. Finally, it is interesting to see that the minimum values for the IV across the different time periods is relatively static, ranging from 14.6% to 13.0%. On the contrary, the maximum values for the IV across the different time periods are much more diverse, ranging from 243.6% to 57.0%. This could be explained by the fact that the IV over different time periods may react more diversely to circumstances that could increase the degree of uncertainty in the market. This, in turn, may be explained by the fact that the market expects certain shocks of uncertainty to be resolved within a certain time period, thus affecting the IV over some time periods, while not affecting the IV over time periods beyond that. However, since the minimum values across the different time periods are mostly similar, it could be the case that circumstances of certainty affect IV over the different time periods similarly. However, it may also be the case that there is a certain baseline degree of uncertainty that is not specific to a time period, thus resulting in the similar values for IV over the different time periods.

Table 9: Descriptive statistics on IV for different time periods

Variable	Observations	Mean	St. Dev.	Min.	Max.
IV1M	121	.375	.273	.146	2.436
IV2M	121	.367	.245	.144	2.092
IV3M	121	.359	.173	.145	1.262
IV6M	121	.346	.14	.146	1.244
IV9M	121	.327	.101	.145	.68
IV1Y	121	.315	.09	.145	.68
IV2Y	121	.264	.07	.141	.452
IV3Y	121	.242	.055	.135	.436
IV4Y	121	.249	.097	.134	.901
IV5Y	121	.253	.177	.13	1.594

3 Methodology

3.1 Option prices and implied volatility (IV) in the Generalized Black-Scholes model

In order to determine the implied volatility of an oil future contract, one can apply the Black-Scholes option contract pricing formula (Scholes & Black, 1973) to the data on the oil option contract prices. Other forms of the Black-Scholes formula have been proposed, such as the Merton iteration, which also accounts for dividend yields from the underlying asset (Merton, 1973). This more detailed version takes into account dividend yields on the underlying asset in the pricing of an option contract. However, since the asset in this analysis is a commodity that does not generate traditional dividend yields, the version by (Merton, 1973) may not be the most appropriate. However, commodities as an asset class have the potential of incurring storage costs, which may be viewed as negative dividend yields on the commodity asset. This notion will be introduced into the methodology at a later point as part of the concept of a so-called cost-of-carry rate that is applicable in the context of commodity assets. Another version of this formula was put forward by Ingersoll Jr (1977), which accounts for transaction costs and tax shields. However, since the underlying asset is not a stock or bond, there are no real consequences with regard to tax shields, and since the derivative contracts financial markets are generally efficient, transaction costs are assumed to not have a significant impact in this paper's context. Therefore, the Black-Scholes options contract pricing formula is as shown in equation 1 and 2 below:

$$C = S * N(d_1) - X * e^{-rt} N(d_2) \tag{1}$$

$$P = X * e^{-rt} N(-d_2) - S * N(-d_1) \tag{2}$$

Where:

- C = the price of the Call option
- P = the price of the Put option
- S = the price of the underlying
- X = the exercise price of the option
- σ = the volatility of the underlying asset (as percent per annum)

- t = the time to expiration of the contract (as a percentage of year), in other literature also defined as (T-t), representing the time to options contract expiration date in years
- r = the continuously compounded risk free rate

d_1 and d_2 are defined as follows:

$$d_1 = \frac{ln\left(\frac{S}{X}\right) + t\left(r + \frac{\sigma^2}{2}\right)}{\sigma\sqrt{t}} \tag{3}$$

$$d_2 = d_1 - \sigma\sqrt{t} \tag{4}$$

And $N(x)$ is the standard normal cumulative density function:

$$N(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{\frac{-t^2}{2}} dt \tag{5}$$

However, since the underlying asset in the context of this paper, crude oil, is a commodity, one should also consider the costs of holding this commodity in inventory, also referred to as the cost-of-carry rate. This introduces a new parameter into the previously mentioned Black-Scholes formulae (formulae 1 and 2), namely the parameter b, which represents the total cost of carrying the underlying asset. As different underlying assets also have different costs of carrying said assets, this parameter b takes on different definitions across different assets. For options contracts on a given non-dividend yielding stock, this parameter b is equal to r_f, or the risk-free interest rate. However, other assets, such as foreign currency assets, dividend-yielding assets and commodity assets are associated with other sources of costs of carrying the investment. For example, the parameter b in options pricing models is equal to $r_f - d$ (risk-free interest rate minus the dividend yield on the underlying asset) for proportional dividend-yielding assets and equal to $r_f - r_f^*$ for foreign currency assets (risk-free interest rate in the domestic country minus the risk-free interest rate in the foreign country), as summarized by Barone-Adesi and Whaley (1987). In the case of commodities, these additional costs of carrying can include physical storage costs of the asset, but also other sources of costs, such as insurance costs. These additional costs of carrying are then included in the Generalized Black-Scholes (GBS) options pricing formula through parameter $b = r_f + c$ (Black, 1976), as shown in equations 6 and 7 below, which are extensions on equations 1 and 2:

$$C = Se^{ct} * N(d_1) - X * e^{-rt}N(d_2) \tag{6}$$

$$P = X * e^{-rt}N(-d_2) - Se^{ct} * N(-d_1) \tag{7}$$

Where c represents the aforementioned costs of carrying associated with holding the underlying asset and d_1 and d_2 are defined as follows:

$$d_1 = \frac{ln\Big(\frac{S}{X}\Big) + t\Big(r + c + \frac{\sigma^2}{2}\Big)}{\sigma\sqrt{t}} \tag{8}$$

$$d_2 = d_1 - \sigma\sqrt{t} \tag{9}$$

And $N(x)$ is still the standard normal cumulative density function:

$$N(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{\frac{-t^2}{2}} dt \tag{10}$$

Inverting the relevant Black-Scholes formula, formula 6 for call options and formula 7 for put options, so that σ (the volatility of the underlying asset) is the only parameter on the left-hand side of the equation, gives us a formula with the price-implied volatility as the dependent variable. However, since the inverse function of pricing equations such as these does not always yield a closed-form solution, a root-finding method or iterative search method is needed to generate a solution for the implied volatility of an options contract. However, as mentioned before, this data has already been calculated and provided by the Eikon Datastream platform.

3.2 Country and political risk

After collecting the data on risk scores for the countries mentioned in table 1, the data on risk scores for all countries in a subcategory will be condensed into a composite risk score that will represent the risk in that specific subcategory for the specific time period. In order to quantify the risk situation in the oil-exporting and importing countries, I will be making use of the risk scores data as described in the data section. Firstly, I will be transforming these individual scores into composite scores for each of the 4 sub-sets of countries listed in table 1 to allow for analyses on the effect of risk in countries with different types of roles in the global crude oil market, on the price of crude oil and the implied volatility of oil options contracts. I will do so by transforming the countries' individual risk scores into a composite political risk score of all countries in one of the given sub-sets, by calculating the average of the political risk scores, as weighted by the scale of oil production (or oil imports for the subcategory of non-OPEC importers) of each of the individual countries. This will be done by making use of formula 11 for each subset containing k countries:

$$CompositeRisk_t = \sum_{n=1}^{k} RISK_{k,t} * \frac{OIL_{k,t}}{\sum_{n=1}^{k} OIL_{k,t}} \tag{11}$$

Where:

- $CompositeRisk_t$ = the calculated composite risk score for a given subcategory in time period t
- $RISK_{k,t}$ = the individual risk score of country k
- $OIL_{k,t}$ = country k's oil exports or imports (depending on the subcategory)

This transformation will transform the variable country risk score (CRS) into the variable composite monthly country risk score (CMCRS) and the variable political risk score (PRS) into the variable composite annual political risk score (CAPRS).

3.3 Regression analysis: GARCH

In order to investigate this paper's hypotheses, I will be making use of a regression. The most common form of the regression, the Classic Linear Regression Model (CLRM), is used to model the relationship between multiple variables. In doing so, the CLRM relies on several fundamental assumptions that ensure the validity of the conclusions drawn from the regression. One of these fundamental assumptions is the assumption of homoskedasticity across the data, which assumes that the variance of the error terms across the data is constant. Violation of this assumption introduces some concerns that need to be considered. In cases where homoskedasticity mistakenly is assumed to be present (i.e. the variance of the error terms is in fact not constant across the data, which is also referred to as heteroskedasticity), the coefficients in an ordinary least squares (OLS) regression are still unbiased. However, traditional methods, as generally used in the context of an OLS regression, will not be appropriate for calculating the standard errors in this case and will lead to incorrect results for the statistical tests of significance and could thus impair the precision of the findings (Engle, 2001). The phenomenon of heteroskedasticity is especially important in the context of economics and in particular financial markets. This is caused by the fact that these contexts in particular often experience time periods where the volatility of the error terms is significantly different. One of the most well-known examples of causes of heteroskedasticity in these contexts is the 2008 financial crisis, which saw a relatively short-lived period of increased volatility (Schwert, 2011). This short period of "uncharacteristic" volatility levels would then potentially introduce heteroskedasticity into regressions on data sets that include and extend beyond this time period, affecting the standard error calculation of such a regression and the precision of statistical testing. There are many econometric methods available that can be used in the case of heteroskedasticity, such as heteroskedasticity-consistent standard error estimates or logarithm transformation on variables (Brooks, 2019). Another popular and commonly used method in financial applications is the Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) model introduced by Bollerslev (1986). Where other models try to accommodate for the heteroskedasticity, a GARCH model instead attempts to model the heteroskedastic volatility of the error terms. It does so by modelling the variance as being conditional, i.e. it is modelled as being partly determined by its previous values (lags) and any past information that is considered to be relevant. In doing so, a GARCH model is quite similar to an Auto Regressive Moving Average (ARMA) model, however, an ARMA model specifies the conditional mean in a (semi-) stationary series, where the GARCH model specifies the conditional variance. Doing so allows for minimizing the errors in situations where the volatility of the error terms is not constant, thus improving the calculation of the standard errors and the precision of any statistical tests that rely on these standard errors. Another important consideration is the potential existence of autocorrelation in the time series data. Autocorrelation refers to a situation where a time series of a variable is correlated to itself, which means that previous values of that time series contain information on the current value of that variable's time series (Brooks, 2019). An important assumption of the OLS model is that the individual observations (e.g. over time) are independent of each other. This would then mean that the error terms of individual observations should not be correlated to each other. In the case of autocorrelation, however, the error terms of individual observations may actually be correlated to each other, as consecutive observations' values are correlated to each other and thus the error terms are likely correlated to each other as well. This phenomenon of auto correlation could thus violate one of the major assumptions of the OLS model, and could therefore lead to incorrect conclusions being drawn from the results of these models. However, the GARCH model allows for the modelling of the error variance, and can thus also be used to counter the problem of auto-correlated error terms, as the variance in the error terms is estimated through the GARCH model (Brooks, 2019). A GARCH model in its simplest form (i.e. a GARCH(1,1) model) can then be formed as shown in equation 22:

$$y_t = x_t b + \epsilon_t \tag{12}$$

Formula 12 represents the general regression equation, with y_t as the dependent variable, x_t as the independent variable, b the coefficient for the independent variable and ϵ_t being the error term in the regression. Next, ϵ_t can be defined as follows:

$$\epsilon_t \sim N(0, \sigma_t^2) \tag{13}$$

Then, the conditional variance σ_t^2 under GARCH(1,1) methodology, is defined as in equation 22:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 + ... \tag{14}$$

Where σ_t^2 is the conditional variance, α_0 is a term capturing a long-term average value for the variance, $\alpha_1 u_{t-1}^2$ is the term containing information on the previous period's volatility, and $\beta\sigma_{t-1}^2$ is the term containing information on previous period's fitted value for the conditional variance, as determined by the GARCH model. The right end of the equation is open-ended (as denoted by the "+ ..."), as more lags can be incorporated into the GARCH model, either for the previous periods' volatility or the fitted value for the conditional variance. However, I will be making use of a GARCH(1,1) model, as this is generally sufficient to accommodate any potential clustering of volatility in the data set (Brooks, 2019).

Next, I will be applying the previously discussed GARCH model to the context of this analysis. As such, I will construct two GARCH models, one for the analysis of crude oil prices and CRSs, and one for the analysis of crude oil options contracts price implied volatility and CRSs. These two GARCH models will be discussed in the next subsections. In these GARCH models, the error term in the main regression equations is specified according to the specification mentioned in equations 12 and 22. As a method of preliminary testing the regression models that will be applied, I will be performing a joint significance test on both of the following two regression models. The joint significance test is a test that is aimed at testing whether all of the coefficients in the regression model are jointly significant, meaning that at least one of the included coefficients is not equal to zero. This test, which is used as a first preliminary check to ensure the meaningfulness of the regression model, is also referred to as the overall regression F-statistic, referring to the F-test statistic that is being used to assess the significance in this test.

3.3.1 Regression analysis on crude oil prices and CRSs

The first analysis to be carried out, on the relationship between each individual subcategory's CRS and crude oil prices, will be investigated by making use of regression equation 15:

$$P_t = \beta_0 + \beta_1 OPEC_t + \beta_2 OPECPL_t + \beta_3 EXP_t + \beta_4 IMP_t + \beta_5 VOL_t + \beta_6 OI_t + \epsilon_t \quad (15)$$

With ϵ_t specified as follows:

$$\epsilon_t \sim N(0, \sigma_t^2) \quad (16)$$

$$\epsilon_t = u_t^2 - \sigma_t^2 \quad (17)$$

And with σ_t^2 specified as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (18)$$

Where:

- P_t = the crude oil price per barrel in period t
- $OPEC_t$ = the weighted average CRS of subcategory OPEC in the current period t
- $OPECPL_t$ = the weighted average CRS of subcategory OPEC+ in the current period t
- EXP_t = the weighted average CRS of subcategory Non-OPEC exporters in the current period t
- IMP_t = the weighted average CRS of subcategory Imp in the current period t
- VOL_t = the trading volume in the options instrument in the current period t
- OI_t = the open interest in the options instrument in the current period t
- ϵ_t = the error term as specified in the GARCH model in equation 12 and 22
- u_t = the residual term of the conditional variance estimation

3.3.2 Regression analysis on crude oil options contracts price implied volatility and CRSs

The second analysis on the relationship between the subcategories' CRSs and oil options contracts' price implied volatility will be investigated through the regression equation listed in formula 19 below:

$$IV_t = \beta_0 + \beta_1 OPEC_t + \beta_2 OPECPL_t + \beta_3 EXP_t + \beta_4 IMP_t + \beta_4 VOL_t + \beta_5 OI_t + \epsilon_t \quad (19)$$

With ϵ_t specified as follows:

$$\epsilon_t \sim N(0, \sigma_t^2) \quad (20)$$

$$\epsilon_t = u_t^2 - \sigma_t^2 \quad (21)$$

And with σ_t^2 specified as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (22)$$

Where:

- IV_t = the implied volatility as implied by the price of crude oil options contracts in period t
- $OPEC_t$ = the weighted average CRS of subcategory OPEC in the current period t
- $OPECPL_t$ = the weighted average CRS of subcategory OPEC+ in the current period t
- EXP_t = the weighted average CRS of subcategory Non-OPEC exporters in the current period t
- IMP_t = the weighted average CRS of subcategory Imp in the current period t
- VOL_t = the trading volume in the chosen options instrument in the current period t
- OI_t = the open interest in the options instrument in the current period t
- u_t = the residual term of the conditional variance estimation

3.4 Diagnostics

Before each regression analysis will be carried out, several diagnostics will be conducted in order to assess potential issues and other characteristics of the data that may need consideration.

3.4.1 Reverse causality

In this paper, the analysis is primarily aimed at investigating the potential effect that country and political risk have on crude oil implied volatility and prices. However, as previously discussed, the dynamics of the crude oil market can also have very significant economic and political effects on countries that are heavily involved in the crude oil market, either on the demand or the supply side. As an example, one can imagine that plummeting oil prices could have a negative effect on the economic and political situation in countries that export significant numbers of crude oil, as the ceteris paribus value of their imports has decreased because of the falling crude oil prices. This could mean that there may be a case of reverse causality present, where the crude oil market also affects the risk situation in certain countries. As regressions are generally only useful in revealing correlations between variables, and causality is not something that can be proven by them, correlations cannot be easily interpreted as being evidence of causality. In order to potentially strengthen insights extracted from the eventual findings of this paper, I will conduct a Granger causality test, in order to gain more insight into the relationship between country and political risk on the one hand, and crude oil prices and implied volatilities on the other hand. The Granger causality test, as coined by Granger (1969), is a statistical test designed to show whether a time series of one variable can be used to forecast the time series of another variable. It does so by generating an auxiliary regression model using lags of either variable and statistically testing whether these lagged values of either variable contain information on future values of the other variable. When these values contain information on future values of the other variable, the Granger causality test provides evidence for the case that one variable precedes the other, meaning that it can be used to forecast values of the second variable (Granger & Newbold, 2014). The Granger causality test auxiliary regression in its general form is displayed in formula 23:

$$y_t = a_o + a_1 y_{t-1} + a_2 y_{t-2} + ... + a_m y_{t-m} + b_p x_{t-p} + ... + b_q xt - q + \epsilon_t \tag{23}$$

In this equation, y_t is the dependent variable in the main regression equation and x_t are the explanatory variables, and lags of both are included in the regression. If the auxiliary regression model in formula 23 returns any individually significant coefficients for any of the lagged parameters of x, then it cannot be said with certainty that x does not Granger-cause y, and only in the case where all the lagged x parameters return individually insignificant coefficients is the null hypothesis accepted that states that x does not Granger cause y.

In order to perform the Granger test of causality, I will first estimate a Vector Auto-Regressive (VAR) model. These types of models are generally used for modeling relationships between multiple dependent variables which are included in these simultaneous equations structural models (Brooks, 2019). This VAR model will be conducted several times, once for each of the dependent variables in all GARCH models, namely crude oil prices and the implied volatilities over the 10 different relevant time periods, ranging from 1 month to 5 years. Additionally, these VAR models will include 2 dependent variables each, namely the dependent variable from the GARCH analyses and the variable that was found to be statistically significant. All these variables will be considered as endogenous variables in the VAR model. The value of each dependent variable will be regressed on its own previous values, as well as the values of the other dependent variables included. This is shown mathematically in equation 24 below (Brooks, 2019):

$$y_{1t} = \beta_{10} + \beta_{11} y_{1t-1} + ... + \beta_{1k} y_{1t-k} + \alpha_1 1 y_{2t-1} + ... + \alpha_{1k} y_{2t-k} + u_{1t} \tag{24}$$

In order to select the optimal number of lags to include in this VAR model, I will rely on the Akaike Information Criterion (AIC) to make the optimal choice. The AIC is an information criterion that is aimed at assessing the quality of a model and also contains a factor that punishes models for including too many parameters. After generating these models with varying numbers of lagged values, I will select the model with the lowest AIC score as models with lower AIC scores are often seen as better in terms of performance.

3.4.2 Hold out sample and validity

After constructing the functional regression models, it would be interesting to know whether these models would perform well in forecasting and analyzing the data in the used data set. One method of analyzing the models' performance on the used data set is by making use of a so-called hold-out sample. The way this method functions is by firstly estimating the regression models on one (relatively large) section of the data set and withholding a small section and then using the parameters estimated by these regression models to estimate the fitted values for the data section that was previously withheld. This essentially tests the internal validity of the models by analyzing whether the estimated relationships for a large section of the data set would perform well in predicting the values of the dependent variable in a smaller section of the data that was not included in the estimation of the regression models. Then, if the fitted values for the smaller data section do not differ greatly from the observed values for that section of data, evidence is provided for the fact that these regression models accurately estimate the relationship between the variables in the data set. If the fitted values and observed values for this smaller section of data differ greatly, then the models do not perform as well in predicting the dependent variable's values in the data set, which could be evidence of lowered internal validity. I will perform this method by estimating the main regression equation on the time period ranging from the year 2012 until August 2021 and then comparing this with the hold-out sample ranging from September 2021 until the end of the data set in August 2022.

After all regression analyses have been carried out, interpretation of the fitted coefficients, their statistical significance, and their theoretical implications will follow.

3.5 Non-parametric analysis on political risk

The final formal analysis of this paper, as mentioned, will be a non-parametric analysis of the political risk data for all the subcategories. This set of data consists of annual observations on the independent variables, namely the CAPRS for all the relevant subcategories of countries and the average annual values for the dependent variables, namely crude oil price and the implied volatility of the crude oil options contracts. All of these annual observations range from the year 2012-2022. To this end, I have opted to employ the non-parametric Theil-Sen (TS) estimator, as coined by (Theil, 1950) and elaborated on by (Sen, 1968), to estimate the linear effect of subcategories' CAPRS on the annual average values for the dependent variables, crude oil price, and crude oil options contracts' implied volatility. The TS estimator has been shown by Ohlson and Kim (2015) and Wilcox (1998) to perform quite well as compared to OLS, even in situations that should be ideal for an OLS approach (Wilcox, 2001). Moreover, the TS estimator has been shown to be robust even in the presence of outliers in the sample (Shah, Rehman, Rashid, Karim, & Shah, 2016).

The TS estimator functions by estimating the median slope from the sample of slopes calculated from all possible pairs of observations. The TS estimator can be mathematically represented as follows in equation 25:

$$TS = median\{(y_j - y_i)/(x_j - x_i)\} \tag{25}$$

For all pairs (i, j) in the set of data. This TS estimator will be estimated for all combinations of independent variables (price and the 10 definitions of implied volatility) and dependent variables (the composite political risk scores for the 4 subcategories of countries).

The TS estimator is a non-parametric method used to estimate the slope of a linear relationship in a sample. In this case, the TS estimator will be used to estimate the slope of the linear relationship between the CAPRS of each of the 4 subcategories as the independent variable, and the variables *Price* and all time periods of IV as the dependent variables.

Because the data are temporal and have a natural ordering, we will use a bootstrap method for hypothesis testing. The bootstrap involves resampling the observed data with replacements to generate new sets of data, from which we can compute the TS estimator for each resample. This methodology will allow statistical testing of the TS estimator, with the null hypothesis stating that there exists no linear relationship between the two variables involved, and the alternative hypothesis stating that a linear relationship does exist.

By generating many replicate datasets, the bootstrapping process creates a distribution of sample statistics, such as means or standard errors, that can be used to estimate population parameters or assess the variability of the sample statistic. Additionally, one of the advantages of bootstrapping is that it does not require any assumptions about the distribution of the data, which makes it particularly useful for non-parametric methods, such as the Theil-Sen estimator.

As such, firstly the TS estimator will be calculated for the observed data in the original dataset. This calculated value for the TS estimator will also constitute the test statistic. Afterward, a large number of bootstrap resamples of the observed data will be generated, each with the same number of observations as the original dataset. Then, for each of these bootstrap resamples, the TS estimator will also be calculated. Then, the aforementioned test statistic will be used to calculate the p-value, which is equal to the proportion of the bootstrap resamples where the test statistic (i.e. the value of the TS estimator in those bootstrap resamples) is greater than or equal to the observed value in the original data set. Afterward, this p-value will be compared to the traditional confidence levels.

4 Results

4.1 Calculated CMCRSs

As mentioned, the country risk scores per individual country originally included in the data set will be transformed into composite monthly country risk scores (CMCRS) for each of the previously defined subcategories of countries according to the methodology mentioned in section 3.2. This transformation yielded time series on each of the 4 subcategories' CMCRS, ranging from August 2012 through August 2022, graphically shown in figure 1. These time series on each of the subcategories' CMCRS will then be incorporated into the following analyses.

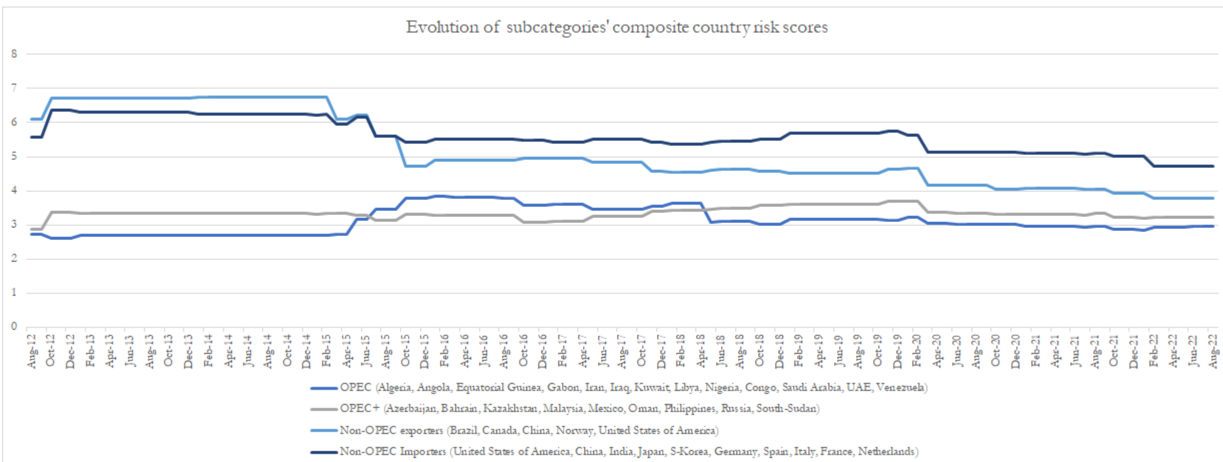

Figure 1: Timeseries of each subcategory's composite CRS

4.2 GARCH

4.2.1 GARCH analysis on crude oil price

The following section will present the results yielded from the GARCH analyses that were performed. Firstly, the results that were retrieved from the estimation on the hold-in sample ranging from August 2012 to August 2021 will be presented and interpreted. Afterward, the estimated coefficients from the estimated model will be used to predict the values for the relevant dependent variable over the duration of the hold-in and the hold-out sample. Then, the predicted values and actual values of the relevant dependent variable will be compared to provide a conclusion on the hold-out sample analysis. Finally, the Granger-causality test will be performed in the cases where a statistically significant relationship is identified between a dependent and independent variable.

I will continue with estimating the GARCH(1,1) model that models the price of crude oil according to the regression formula shown in equation 15. The output resulting from this GARCH(1,1) model is shown in table 10 below:

Table 10: Results from the GARCH regression on crude oil price

price	Coef.	St. Error	t-value	p-value	[95% conf.	interval]	Sig.
OPEC	-14.211	5.795	-2.45	.014	-25.57	-2.852	**
OPECPL	-7.494	22.421	-0.33	.738	-51.439	36.45	
IMP	13.990	23.593	0.50	.553	-32.251	60.232	
EXP	5.665	10.884	0.52	.603	-15.668	26.997	
Open interest	.000	.000	-0.94	.348	.000	.000	
Trading volume	-.006	.002	-2.80	.005	-.009	-.002	***
Constant	32.798	45.17	0.73	.468	-55.733	121.329	
Mean dependent var	63.426						
Observations	108						
Prob > chi 2	0.000						
Akaike Criterion (AIC)	860.898						

**** $p < .01$, ** $p < .05$, * $p < .1$*

In this table, we can see the estimated coefficients for the independent variables and their associated p-values. As we can see in the table, the joint significance test returns a p-value of .000, thus providing strong evidence that at least one of the included variables is not equal to zero and that all included coefficients are jointly significant. The first variable reporting a coefficient that is found to be significant on the 5% confidence level is *OPEC*, with a reported coefficient of -14.211 and a p-value of .014. The estimated coefficient of -14.211 implies a negative relationship between the CMCRS for the OPEC subcategory, meaning that a 1-point increase in the CMCRS for the OPEC subcategory, on average, is associated with a decrease in the price per barrel of crude oil of 14.211 US dollars. Since an increase in the CMCRS signifies that the level of country risk in the relevant subcategory has decreased (thus being more stable), we can further interpret this finding as constituting statistically significant evidence that a decrease in the level of country risk in the *OPEC* subcategory (i.e. country risk has decreased and the country risk situation has become more stable) is associated with a decrease in the price per barrel of crude oil in this data set.

Next, I will compare the values predicted for the dependent variable *price* through the estimated model with the actual values of the variable *price*. This comparison can be seen in figure 2 below, in which the threshold for the hold-in and hold-out sample (August 2021) is denoted by a vertical line. Moreover, the predicted values for the dependent variable *price* are denoted by the blue line and the actual values for the dependent variable *price* are denoted by the red line.

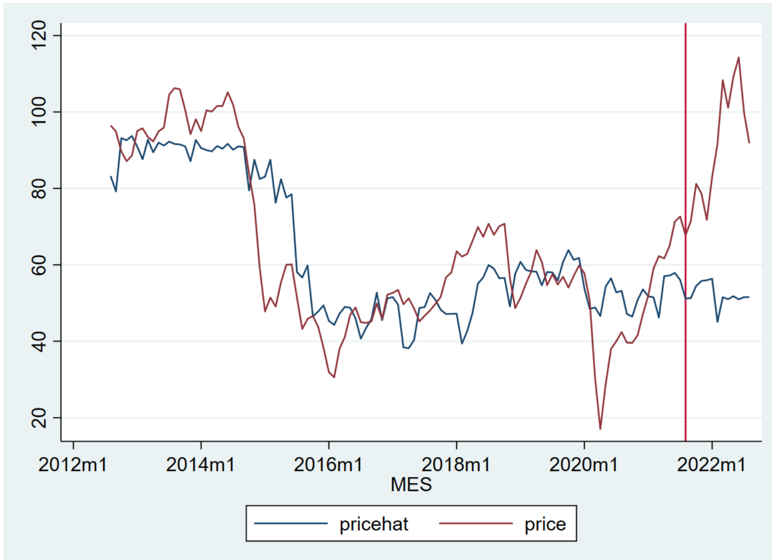

Figure 2: Model-predicted (*pricehat*) and actual values for *price*

In figure 2 we can see that the predicted and actual values for the dependent variable *price* tend to be relatively close to each other for the duration of the hold-in sample ranging from August 2012 to August 2021. However, the two series clearly deviate for the duration of the hold-out sample ranging from August 2021 through August 2022. This provides evidence for the fact that the model estimated over the hold-in sample would not be able to perform well when confronted with new data. This is likely caused by overfitting on the data in the hold-in sample. This means that the findings estimated by the model over the hold-in sample are unlikely to hold in other samples of data and contexts.

4.2.2 GARCH on Implied volatility

The next set of analyses will consist of GARCH analyses with the same independent variables, but now the dependent variable will be the implied volatility (IV) of crude oil options contracts. As IV is determined based on a certain time period, this analysis will be performed for all time periods for which the IV is defined, ranging from 1-month to 5-year IV. The coefficients on all subcategories' CMCRS and their associated statistical significance following from the GARCH analyses are summarized in table 11. As the IVs are measured in percentages, the coefficients in table 11 also translate to percentage increases (decreases) associated with a 1-point increase (decrease) in the independent variables, which are the subcategories'

CMCRS.

Table 11: Summarized results of GARCH analyses on all definitions of *IV*

y	OPEC	OPECPL	IMP	EXP	Open Interest	Tr. Volume
IV1M	-1.958	-43.206***	20.717***	-13.069***	.000	.000
IV2M	8.313***	51.624***	31.098***	-19.298***	.000	.006***
IV3M	1.223	14.834**	36.063***	-21.421***	.000	.004***
IV6M	6.540***	37.159***	-38.236***	12.318***	.000	.003***
IV9M	-.399	22.016*	-31.641**	8.76*	.000	.000
IV1Y	15.976***	18.700***	-18.800***	5.348***	.000	-.002***
IV2Y	.487	-9.410***	6.678**	-6.314***	.000	.000*
IV3Y	1.949***	-1.168	-.286	-3.160***	.000	.000***
IV4Y	-.740	3.869*	-10.155***	.522	.000***	-.000
IV5Y	4.263***	16.937***	-16.153***	6.401***	.000***	-.000

*** $p < .01$, ** $p < .05$, * $p < .1$

In table 11, we can see that the analyses yielded quite some statistically significant results, with many even significant on the 1% confidence level. Many of the reported coefficients (which represent percentage increases or decreases in the relevant time definition of IV) are not only of statistical significance but also of economic significance, with many of the statistically significant coefficients reporting an absolute magnitude of over 30%. This constitutes a very significant result given the usual ranges in which IVs tend to move. For instance, when looking at the coefficient for *OPECPL* on *IV1M* in the second column of table 11, we can see that the coefficient for *OPECPL* in the analysis on *IV1M* is equal to -43.206 while being statistically significant even on the 1% confidence level. This coefficient translates to a 1-point increase in the *OPECPL* subcategory's CMCRS being associated, on average, with a -43% decrease in the 1-month implied volatility and consequently market uncertainty. Since an increase in the CMCRS means that the level of country risk has decreased, this thus translates to a decrease in the *OPECPL* subcategory's level of country risk (and thus an increase in its CMCRS) being associated with a -43% decrease in the 1-month implied volatility and market uncertainty.

Given the fact that the four categories are all important actors in the global crude oil market, either on the supply (*OPEC, OPECPL, EXP*) or the demand (*IMP*) side, it is expected that the results will suggest a link between each categories' CMCRS and the different time definitions of implied volatility. More specifically, conceptually it would be very logical to expect negative coefficients for each category's CMCRS on the implied volatilities, as increased levels of country risk in any subcategory (which would translate to decreases in

CMCRS) would be associated with increases in IV and market uncertainty as a consequence of these categories' important role in the global crude oil market. However, as will be discussed next, we can see that this does not hold for all reported coefficients and that we can see some interesting phenomena across the different coefficients for each subcategory.

Starting with the first independent variable, we can see that the coefficients for the variable *OPEC* display relatively fewer statistically significant results with only half of the coefficients being statistically significant, whereas the three other variables almost exclusively report statistically significant coefficients. Additionally, the coefficients for *OPEC* are much smaller in magnitude than those for the other variables, and all coefficients for *OPEC* are positive.

The smaller magnitude of *OPEC*'s coefficients may be a result of the dynamics between the category's countries and the market for crude oil, as compared to the countries in the other subcategories. It could be the case that the markets believe that changes in the country risk situation in OPEC countries have less of an effect on the global crude oil market, explaining the smaller impact on IV and market uncertainty. This may seem counterintuitive given the important role that OPEC plays in the global crude oil market. However, it could be the case that the seemingly smaller impact of *OPEC*'s CMCRS can be explained by the fact that the *OPEC* influences the global crude oil market in a different way compared to the other categories. The OPEC influences the global crude oil market through internationally designated policies, which its members comply with. The other categories, however, influence the global crude oil market on a more individual level. As an example, consider the case of a country with a high weighting in the calculation of the CMCRS and the country belonging to either the *OPEC* or *EXP* category. In the event of a large shock to that country's individual country risk situation that also affects its oil production, it is likely that it would affect that country's operations in the global crude oil market, and given the country's importance for the market, would also impact the global market for crude oil. If this country would belong to the *OPEC* subcategory, it is likely that the country would have less discretion in altering its operations in the crude oil market as compared to the situation where that country would belong to the *EXP* category, since there would be OPEC policy the country has to adhere to. However, whether this is actually a (partial) explanation for the differences in magnitude between the categories cannot be said with certainty based on these results, but could be an interesting direction for future research.

Additionally, it is very interesting that all of the statistically significant *OPEC* coefficients are positive in sign, as *OPEC* is the only variable with exclusively positive statistically significant coefficients. As previously discussed, it would be a very logical expectation to see mostly negative coefficients. The fact that all statistically significant coefficients are positive in sign could mean that there is some other dynamic at play than the one hypothesized before. The positive coefficients for *OPEC* means that an increase in the *OPEC* category's CMCRS and a decrease in the level of country risk are associated with an increase in the implied volatility or market uncertainty in the global crude oil market, which seems quite counterintuitive. This seems counterintuitive, as it implies that a source of uncertainty on the country level (as represented by country risk) is associated with more certainty in the global crude oil market in which that country operates. The absence of the previously hypothesized relationship could be partially explained by the notion that, for the *OPEC* category, the individual countries' operations in the global crude oil market are relatively more detached from the individual countries' country risk situation through OPEC policy. However, this would still not explain the reported coefficients with signs opposite to what would be expected from the hypothesized relationship. Instead, it could be the case that the answer lies in the way in which OPEC policy addresses increases in individual OPEC countries' country risk levels. It could potentially be the case that OPEC policy aimed at stabilization of the global crude oil market is so effective in these cases where an individual constituent's country risk is increasing, that it leads to an overshooting decrease in the market uncertainty in the global market for crude oil. This may seem far-fetched, but it could be fruitful for future research to investigate how OPEC policy changes are received by the global crude oil market, and whether these policy changes increase or decrease the level of market uncertainty.

Finally, it seems that the coefficients for *OPEC* are greater for the shorter time definitions of IV. As such, it seems that *OPEC*'s CMCRS seems to have a stronger effect on the longer time definitions of implied volatility. This could mean that crude oil markets believe that the consequences of an increase in CMCRS in the *OPEC* subcategory will be relevant for the shorter time definitions of implied volatility, but will resolve in the longer term.

Next, looking at the reported coefficients for the variable *OPECPL* shows that almost all coefficients are statistically significant on some level, with seven of them statistically significant on at least the 5% confidence level. Further inspection of the coefficients shows that the magnitude of *OPECPL*'s statistically significant coefficients is much larger than that of *OPEC*'s coefficients. However, given the close integration of the OPEC and OPEC+ organizations, it seems unlikely that there are differences in how these two subcategories affect the global crude oil market. As such, finding possible explanations for this huge difference seems difficult. Perhaps, it could be the case that the countries included in the *OPECPL* category were allowed more discretion in their operations in the global crude oil market as compared to countries that hold a full OPEC membership. Then, actions going beyond OPEC+ policy could perhaps lead to individual *OPECPL* countries taking additional steps that influence global crude oil markets, thus affecting the level of implied volatility and market uncertainty even more. However, it is hard to come to a conclusive answer to this question using the results from the analyses in this paper. As such, I would recommend future research to further investigate the suggested differences in dynamics with the crude oil markets between the OPEC and OPEC+ countries.

Looking at the *OPECPL* coefficients' signs, it becomes clear that the vast majority of the coefficients are positive in sign, with only two exceptions. Positive coefficients indicate that a decrease in the *OPECPL*'s CMCRS is associated with an increase in the implied volatility and market uncertainty of that specific time definition. The first exception is the negative coefficient for *OPECPL* in the regression on the 1-month implied volatility, which reported a very negative statistically significant coefficient of -43.206. This coefficient is completely different from the other *OPECPL* coefficients, especially given the fact that the *OPECPL* coefficient in the analysis on the 2-month implied volatility is also highly statistically significant, but very positive with a coefficient of 51.624. It seems that this very sudden and massive change in the *OPECPL*'s coefficient between the analyses on the 1-month and 2-month implied volatilities is very hard to explain theoretically. However, it could be the case that changes in *OPECPL*'s CMCRS that the market perceives to have an influence on the market for 1 month only are of a greatly different nature as compared to changes in CMCRS that have effects with longer duration. However, this seems rather unlikely, given the magnitude of the change in the *OPECPL*'s coefficient between the analysis on the 1-month and 2-month implied volatility. As such, it would be interesting for future research to investigate different drivers of changes in CMCRS, and how long these changes continue to have an effect on the global crude oil market.

Finally, it is interesting to note that the *OPECPL* coefficients also seem to be decreasing in magnitude as the time definition of implied volatility becomes longer, as was the case for the *OPEC* coefficients. Indeed, the coefficients that are the largest in magnitude all occur for the implied volatility time definitions up to the 6-month IV. An explanation similar to the one given for the same phenomenon in the *OPEC* coefficients could be applied here, with the markets perceiving that the effects of changes in CMCRS on the global crude oil market uncertainty will resolve themselves in the longer term, thus leading to less impact on long-term IV and market uncertainty.

Looking at the reported coefficients for the variable *IMP* shows that all but one of the ten coefficients are statistically significant on at least the 5% confidence level, with many even being statistically significant on the 1% confidence level. The coefficients seem to be relatively large and stable in magnitude.

However, the sign of the coefficients seems to be less consistent, with approximately half of the coefficients being positive. Looking at the signs of the coefficients, it becomes clear that the coefficients for the shorter time definitions up to the 3-month implied volatility are positive, after which the majority of the coefficients are negative for the longer time definitions of implied volatility. This sign switch after the 3-month implied volatility is quite significant, as the change in coefficient is rather large, going from a very positive coefficient to a very negative coefficient. This could be explained by the duration of the uncertainty that changes in the *IMP* category's CMCRS imposes on the global crude oil market. Based on the signs of the coefficients, the results suggest that increases in country risk levels in the *IMP* category are associated with decreases in the 1-month, 2-month, and 3-month implied volatility and market uncertainty in the global crude oil market. However, for the longer implied volatility durations, the results suggest that an increase in the level of country risk in the *IMP* category would be associated with increases in the implied volatility and market uncertainty for the majority of the longer time definitions beyond the 3-month implied volatility, which agrees with the intuitive expectation for the coefficients as outlined before. The positive coefficients for the shorter time definitions are less straightforward to find explanations for. However, it could be the case that increases in individual *IMP* countries' CRS are tied to changes that alter those countries' operations in the global crude oil market, which in turn could reduce the level of uncertainty. A highly speculative and hypothetical example would be the case where a country belonging to the *IMP* category experiences a shock that increases the country's CRS, while also severely limiting that country's participation in the global crude oil market. Then, through the reduction in that country's participation in the global crude oil market, it could be that the complexity in the crude oil market decreases, which in turn could lead to short-term decreases in the global crude oil market implied volatility and market uncertainty. However, as mentioned, this example is highly speculative and the results of this paper provide no basis for determining whether this is actually a (partial) explanation for the change in sign. Therefore, to be able to draw more valid conclusions on this matter, I propose that future research look into how individual country risk shocks affect that country's participation in the global crude oil market.

Finally, looking at the results for the variable *EXP* shows that eight out of the ten analyses report a coefficient for *EXP* that is statistically significant even on the 1% confidence level. Looking closer at the individual coefficients reveals that the magnitude of the *EXP* coefficients is significantly smaller than that of the coefficients of *OPECPL* and *IMP*. Next, looking at the signs of the coefficients of *EXP* shows that the sign changes relatively frequently across the different implied volatility time definitions. The *EXP* coefficients for the 1-month, 2-month, and 3-month are all negative, after which the sign changes two more times as the implied volatility time definition becomes longer. As such, the coefficients do not paint a very consistent picture regarding the direction of the relationship between CMCRS and implied volatility. However, the fact that the coefficients for the shortest three time definitions of implied volatility are all negative, suggests that increases in the *EXP* category's country risk level are associated with increases in the short-term implied volatility and market uncertainty in the global crude oil market, which is consistent with the intuitive expectation for these coefficients. However, the fact that the coefficients switch multiple times over the different IV time definitions seems hard to explain.

Finally, it is clear that for the *EXP* variable's coefficients, it is also the case that the magnitude of the coefficients is decreasing as the time window for the implied volatility becomes longer. This could be partially explained by the explanations given previously for the other categories.

Next, the results of the hold-out analysis (which was incorporated in each individual analysis on IV) will be discussed. The visual comparisons of the model-predicted values for the dependent variables on implied volatility and the actual values for the dependent variables on implied volatility are given in figure 3 through 12 in the appendix. The main consideration in these visual comparisons between the model-predicted values and the actual values for the dependent variables on implied volatility is seeing whether the two values seem to be (roughly) similar for the duration of the hold-out period. If this is the case, then this provides some evidence that the model estimated in the GARCH analysis would perform relatively well when confronted with new sets of data. However, when looking at the visual comparisons in figure 3 through 12 in the appendix, we can see that these two values seem to be similar for less than half of the ten analyses.

As such, this actually provides evidence that the models estimated in the GARCH analyses would not perform well at all when confronted with new sets of data, thus meaning that the results and conclusions drawn from the analyses are specific to the exact data sets used. This divergence could be due to the fact that the model estimated in the analyses simply does not hold for the hold-out period because the underlying relationships between the variables have changed due to changing factors. This could be the case since the start of the pandemic in 2020 has thoroughly affected the functioning of the world in many ways. However, a much more likely explanation for this divergence is the phenomenon of overfitting, which means that the models fit the used data set too closely. This is likely caused by the fact that the data set used is relatively small. As such, a straightforward improvement for future research would be to employ a larger data set, in order to mitigate the risk of overfitting and thus improve the ability to draw generally applicable conclusions that are not only applicable to the specific model and data set used.

Meta-analysis of the findings

To conclude the analysis of the categories' CMCRS and the implied volatility, there are some interesting phenomena to note in the results from the GARCH analyses.

First, looking closer at the reported coefficients for *OPEC*, we can see that the mean magnitude of the statistically significant coefficients equals approximately 7.408, with the median equalling 6.540. Additionally, all statistically significant coefficients for the *OPEC* category were positive. As such, it seems that *OPEC*'s CMCRS generally has a slightly positive relationship with implied volatility. Finally, it seems that the coefficients for the shorter time windows up to 1-year IV are higher than those for the longer time windows beyond 1-year IV.

Secondly, looking at the reported results for the *OPECPL* category, several interesting phenomena are revealed. It becomes immediately apparent that the reported coefficients are of a much larger magnitude than those of the *OPEC* category, with the mean of the statistically significant results equalling 12.073 and the median equalling 16.937. Additionally, it is curious that the coefficient for the 1-month IV is a very negative coefficient of -43.206, while almost all other significant coefficients are positive, in most cases by quite some margin. Finally, it seems to be the case that the magnitude of the coefficients (be it a negative or positive coefficient) seems to be larger for the shorter time periods up to the 1-year IV as compared to those of the coefficients beyond the 1-year IV.

Thirdly, inspecting the results for the *IMP* category reveals some interesting features as well. Once again, the magnitude of the coefficients for *IMP* seem to be larger than those for the *OPEC* category, with a mean for the statistically significant coefficients of -2.270 and a median of -10.155. More interestingly, it seems that the sign of the relationship seems to switch from a positive coefficient and relationship up to the 3-month implied volatility to a negative coefficient and relationship beyond the 3-month implied volatility. Additionally, the magnitude of the coefficients seems to decrease significantly for the time periods beyond the 9-month implied volatility while still constantly remaining negative. This could provide evidence for the fact that the *IMP* category's CMCRS's influence on implied volatility changes in sign and magnitude across implied volatility time definitions with differing lengths.

Fourthly, visually inspecting the results for the *EXP* category also reveals some things worth noting. Firstly, the magnitude of the coefficients seems to be somewhat similar to those found for the *OPEC* category, with the mean of the statistically significant coefficients equalling -4.899 and the median equalling -4.737. Contrary to the coefficients found for *OPEC*, the majority of the coefficients for the *EXP* category were reported to be negative. Especially the coefficients found for the time periods up until the 3-month implied volatility are negative by a significant margin, while the coefficients for the time periods beyond 3 months paint a more ambiguous picture, varying between negative and positive coefficients. However, it should also be noted that the coefficients for these longer time periods are much smaller in magnitude than those up until the 3-month implied volatility. This notion seems to suggest that the effect of the *EXP* category's CMCRS on implied volatilities could change depending on the time period for which the implied volatility is defined.

Finally, looking at table 11 it is clear that the magnitude of the coefficients reported in the GARCH analyses seems to be significantly higher for the implied volatility over the shorter time periods. This seems to be in line with the statement in section 2, stating that the values for the implied volatility over shorter time periods seem to be much more volatile than those for the implied volatility over longer time periods.

4.3 Granger-causality testing

As mentioned in chapter 3, the statistically significant results obtained from the previous GARCH analyses will now be tested for Granger-causality in an attempt to find out whether there is evidence for one-directional (where variable X Granger-causes variable Y), two-directional (where variable X and Y Granger-cause each other) or even reverse Granger-causality (where variable Y influences variable X). The summarized results of the statistical significance of these tests, as well as the chosen number of lags included in the Granger-causality tests, are shown below in figure 12.

Table 12: Summarized results of the Granger causality tests

X var. >	OPEC			OPECPL			IMP			EXP		
Y var.	lags	X>Y	Y>X	lags	X>Y	Y>X	lags	X>Y	Y>X	lags	X>Y	Y>X
Price	3	**	-									
IV1M				5	***	***	5	***	*	3	**	-
IV2M	2	-	-	3	-	-	3	-	-	3	-	-
IV3M				3	**	***	3	**	**	3	-	**
IV6M	1	-	-	4	***	-	3	***	-	3	**	-
IV9M				3	**	***	3	***	***			
IV1Y	2	-	-	2	-	**	3	**	-	3	-	**
IV2Y				3	-	-	3	***	-	3	***	**
IV3Y	3	-	**							4	*	***
IV4Y				3	*	-	7	***	-			
IV5Y	4	***	-	4	*	-	2	-	-	5	***	***

****p<.01, **p<.05, *p<.1*

Note. The column $X > Y$ indicates the significance of the Granger causality of X var. on Y var., with the column $Y > X$ indicating the significance of the Granger causality of Y var. on X var. Empty cells indicate no significant results in the GARCH analysis. "-" indicates no significant result in the Granger causality test.

Looking at the results in table 12, some interesting notions come to light. Firstly, looking at the results for *OPEC* in the 2nd and 3rd column of the table reveals that half of the analyses that reported significant coefficients do not provide any evidence for Granger-causality in either direction, which provides evidence for the notion that neither the X nor Y variable is useful in forecasting the other. For the analyses on *OPEC*, it seems that *OPEC*'s CMCRS is only useful in forecasting the independent variable *Price* and the implied volatility over the 5-year time period. Additionally, some evidence is found that in the analysis on the 3-year implied volatility, the 3-year implied volatility may actually Granger-cause the *OPEC*'s CMCRS and would thus be useful in forecasting it. However, since this evidence is reported in only one of the analyses, it seems that in the case of the *OPEC* category reverse causality should not pose a significant problem to the validity of the results and the conclusions drawn from them.

Next, looking at the 5th and 6th columns containing the results for the Granger-causality tests on the *OPECPL*'s category's CMCRS also reveals some interesting details. Firstly, of the nine analyses returning statistically significant coefficients, three of the analyses, provide evidence for the existence of a two-directional Granger causality. This is the case for the analyses on the 1-month, 3-month and 9-month implied volatility. For two of these, namely the 2-month and 2-year implied volatility, no evidence for Granger causality in any direction was found. Three of the nine analyses, namely the 6-month, 4-year and 5-year implied volatility provide statistically significant evidence for *OPECPL*'s CMCRS Granger-causing the implied volatility over their respective time periods. This means that for these time periods, the *OPECPL*'s CMCRS are useful in forecasting the implied volatility. However, it should be noted that the result for *OPECPL* in the 4-year and 5-year implied volatility analyses, is only significant on the 10% confidence level. Finally, the analysis on the 1-year implied volatility finds a statistically significant result for the notion that the 1-year implied volatility Granger-causes the *OPECPL* category's CMCRS. Examining the results over the different time definitions of IV, we can see that most of the evidence for Granger-causality in any direction is present in the shorter time definitions of IV, with only very little evidence beyond the 1-year implied volatility time definition. Perhaps this also provides some evidence that the nature of the relationship between *OPECPL* and IV is not stable over the entire spectrum of time definitions. To conclude, since some of the results denote evidence for a two-directional Granger-causality relationship, it could be that reverse causality hampers the potential to draw conclusions from the results.

Moving to the results for the Granger-causality tests on the *IMP* category in the 8th and 9th columns paints a slightly less ambiguous picture. Four of the nine analyses report evidence for a one-directional Granger-causality existing from the *IMP* category's CMCRS to the 6-month, 1-year, 2-year and 4-year implied volatility time periods. Two of the nine analyses report no statistically significant evidence for a Granger causality in either direction, namely the analyses on the 2-month and the 5-year implied volatility. Three of the nine analyses report some evidence for a two-directional Granger causality existing, namely the analyses on the 1-month, 3-month and 9-month implied volatility. As such, there is some evidence for the fact that reverse causality may be present in some of the analyses, which should be taken into account when drawing conclusions from these results. Additionally, there is relatively more evidence for Granger-causality existing in either direction for the analyses on the *IMP* category, meaning that the variables in these analyses may be relatively more useful when forecasting each other.

Inspecting the results for the *EXP* category in the 11th and 12th columns reveals some ambiguous results. Two of the eight analyses report statistically significant evidence for a one-directional Granger-causality of the category's CMCRS on the implied volatility over the 1-month and 6-month time periods. Two of the eight analyses report statistically significant evidence for a one-directional Granger causality in the opposite direction, namely in the analyses on the 3-month and 1-year implied volatility. Three of the eight analyses provide statistically significant evidence for a two-directional Granger-causality effect existing, which is the case in the analyses on the 2-year, 3-year and 5-year implied volatility. Finally, one of the eight analyses provides no statistically significant evidence for a Granger causality in either direction, namely the analysis on the 2-month implied volatility. For the *EXP* variable, it also seems that the evidence for Granger-causality in any direction seems to differ over the entire spectrum of IV time definitions. More specifically, it seems that most evidence for Granger-causality is present in the longer time definitions. To conclude, there seems to be statistically significant evidence for the potential of reverse causality in three of the eight analyses, which would change the way in which the results are interpreted.

4.4 Theil-Sen estimator analysis on political risk

Next, non-parametric testing was performed on the CAPRS of the subcategories, for which I have used the Theil-Sen estimator. The TS estimator has been calculated for the dependent variable crude oil price, and annual political risk scores of each of the four subcategories of countries. The results of these analyses are shown in figure 13 below:

Table 13: Results of the Theil-Sen analysis on CAPRS and *price* and *IV*

CAPRS	OPEC	OPECPL	IMP	EXP
Price	-10.989	10.989	10.989	-55.556
IV1M	-2.198*	10.989	2.619	2.037**
IV2M	-3.226	4.237	3.226	2.392
IV3M	-3.226	4.237	3.226	2.392
IV6M	-2.618	4.237	3.226	2.392
IV9M	-2.899	3.663	2.392	2.198
IV1Y	-2.618	6.098	2.625	2.037*
IV2Y	-3.226	4.237	3.226	2.392
IV3Y	-2.392	5.000	2.037**	1.667***
IV4Y	-3.663	7.874	2.899	2.618
IV5Y	-3.226	6.098	3.226	2.899

****p<.01, **p<.05, *p<.1*

Looking at table 13, it quickly becomes apparent that only a few of the TS analyses have found statistically significant evidence for a linear relationship existing.

The first analysis that yielded statistically significant evidence for a linear relationship is the analysis on *IV1M*. This analysis yielded a coefficient of -2.198 for the variable *OPEC*, which is statistically significant on the 10% confidence level. As such, this provides evidence for a negative linear relationship between the *OPEC* category's CAPRS and the 1-month implied volatility. More specifically, this result suggests that a 1-point increase in the *OPEC* category's CAPRS is associated with a 2.2% decrease in the 1-month implied volatility. Since an increase in the CAPRS translates to an increase in the level of political risk, thus signifying a less stable political risk situation, this means that an increase in political risk in the *OPEC* category is associated with a decrease in the 1-month implied volatility and market uncertainty.

Secondly, the variable *EXP* also returned a coefficient that is statistically significant, but on the 5% confidence level. This coefficient of 2.037 implies a positive relationship between the *EXP* category's CAPRS and the 1-month implied volatility. More specifically, it means that a 1-point increase in the *EXP* category's CAPRS is associated with a 2.0% increase in the 1-month implied volatility. As such, an increase in the political risk level in the *EXP* category is associated with an increase in the 1-month implied volatility and market uncertainty.

The second analysis that yielded a statistically significant result is the analysis on *IV1Y*. This analysis also yielded a coefficient of 2.037 for *EXP*, statistically significant on the 10% confidence level. This means that a 1-point increase in the *EXP* category's CAPRS is associated with a 2.0% increase in the 1-year implied volatility. As such, an increase in the political risk level in the *EXP* category is associated with an increase in the 1-year implied volatility and market uncertainty.

The final analysis that returned statistically significant results is the analysis on *IV3Y*. The first statistically significant result yielded by this analysis was reported for the variable *IMP*. The variable *IMP* reported a coefficient of 2.037, statistically significant on the 5% confidence level. This means that a 1-point increase in the *IMP* category's CAPRS is associated with a 2.0% increase in the 3-year implied volatility. As such, an increase in the political risk level in the *IMP* category is associated with an increase in the 3-year implied volatility and market uncertainty.

This analysis also returned a statistically significant coefficient for the *EXP* variable. This coefficient of 1.667 is statistically significant even on the 1% confidence level. This coefficient implies that a 1-point increase in the *EXP* category's CAPRS is associated with a 1.7% increase in the 3-year implied volatility. Thus, an increase in the political risk level in the *EXP* category is associated with an increase in the 3-year implied volatility and market uncertainty.

A closer examination of the results of the TS analyses reveals some interesting insights. Firstly, it is interesting that only a few of the analyses returned statistically significant results. Additionally, it is noteworthy to see that these analyses returned coefficients much smaller in magnitude than those found in the GARCH analysis on CMCRS. This may be caused by the fact that the relationship between the CAPRS and the dependent variables is simply much weaker, but could also be caused by limitations in the design of the analysis. Secondly, it is interesting to see that all reported coefficients for the variable *OPEC* are negative, while the other independent variables reported almost exclusively positive coefficients. This suggests that the effect of *OPEC* on the dependent variables may be different than the effects of the other 3 independent variables. However, since none of these coefficients are statistically significant, even on the 10% confidence level, this conclusion cannot be drawn with any statistical certainty.

Comparing the results from the TS analyses with the results obtained from the GARCH analyses shows some potentially interesting insights. The results from the TS analyses show a much more stable picture than those of the GARCH analyses. This is evident by the fact that, for the TS results, there are no sign changes for any of the categories' coefficients over the analyses on different time definitions of *IV*. On the other hand, the results from the GARCH analyses are subject to a much higher degree of change, with all categories' coefficients changing sign at least twice over the different definitions of *IV*. This could mean a couple of things. Firstly, it could simply be the case that the TS results, even though they are insignificant, do provide evidence on what the true relationship between *CAPRS* and *price IV* is. As such, this would imply that the relationship between *CAPRS* and these variables is much more stable than the relationship between *CMCRS* and these variables. More specifically, in the case of the relationship with *IV*, this would mean that the relationship between *CAPRS* and *IV* is less sensitive to changes in the time definition of *IV*. This could be translated to the notion that markets believe that changes in political risk factors underlying changes in *CAPRS* are more persistent over time than changes in country risk factors. However, the ability to draw conclusions from the TS results is limited since the TS results lack statistical significance in the vast majority of the reported coefficients. Secondly, it could also be the case that the variables *CAPRS* and *CMCRS* are actually much more similar than suggested in the previous paragraph, which is also likely given the relatedness of the two underlying concepts as discussed in section 1. If this is actually the case, then it would follow that either the GARCH analyses or TS analyses yielded results that are not representative of the true underlying relationship. Given the large number of statistically significant results in the GARCH analyses and the lack thereof in the TS analyses would suggest that the GARCH analyses are much closer to the true relationship, meaning that the unstable coefficients reported in the GARCH analyses is actually an accurate picture. This would then, assuming the similarity between *CMCRS* and *CAPRS*, mean that the TS results from *CAPRS* is not accurate. This could mean that the TS analysis is not appropriate for investigating the causal relationship in this specific context. In the 6 section, some of these limitations will be discussed.

4.4.1 Sensitivity analysis

Excluding USA from IMP and EXP categories

In section 2, we could see that the United States of America displayed quite some variation in its monthly country risk score. This, combined with the fact that the USA was responsible for a large share of the weight in the *IMP* and *EXP* categories means that this variation in the USA's CMCRS could be a main driving factor behind the outcomes of the analyses. Therefore, it could be interesting to see whether the results differ significantly when the USA is excluded from both these categories. This sensitivity analysis was carried out by removing the USA's CMCRS from the composite risk score calculation, and adjusting the weighting so that the weights totaled 100% after the USA was excluded.

After performing the same GARCH analyses, but now with the CMCRSs calculated without the USA, the results seem to have changed in magnitude but not in sign. The most noticeable change is the fact that 16 of the coefficients have become significantly more positive than they were for the analyses including the USA. In some cases, the increase in the coefficient is as high as approximately 32%, signifying a large change caused by the exclusion of the USA. As such, when interpreting the results of this paper, it should be considered that the results from the original analyses and the conclusions drawn from them are largely dependent on the effect that the USA's CMCRS has in the data set.

The next section of this paper will focus on interpreting the results and linking them to theory.

5 Conclusion

5.1 Political and country risk and its effect on the price of crude oil

The research in this paper was aimed at formulating conclusions regarding two main hypotheses. The first of these hypotheses is as follows:

> *H1: The political risk or country risk in countries that are relevant to the global oil market have an effect on the running price for crude oil in crude oil markets.*

The analyses performed in this paper have provided results that help us make conclusions regarding this hypothesis. Firstly, it was found that there exists a statistically significant negative relationship between the *OPEC* category's level of country risk and the price of a barrel of crude oil. Thus, as the country risk situation in the *OPEC* category becomes more stable, this is associated with a decrease in the price of crude oil. However, there was some evidence that the estimated relationship may be specific to the sample used and potentially would not hold in other settings. On top of that, there was some evidence for the existence of reverse causality in the model.

As such, I conclude that for my specific sample, there is some evidence for the notion that country risk in countries relevant to the global oil market does have an effect on the running price for crude oil. However, more research should be done to investigate whether this finding holds for other sets of data. Additionally, this research could also see if this relationship is indeed exclusive to countries that are members of the OPEC, or that it may also hold for the other categories of countries included in this paper.

Secondly, analysis has found no evidence of any relationship between the categories' political risk score and the price of crude oil. However, it should be noted that the design of the analysis on political risk and the price of crude oil might have been sub-optimal. As such, future research may improve on the methodology applied within this paper in order to further examine this potential relationship.

5.2 Political and country risk and its effect on crude oil implied volatility

The second hypothesis of this paper is as follows:

H2: The political risk or country risk in countries that are relevant to the global oil market have an effect on the market uncertainty in crude oil options contract markets as measured by the implied volatility.

The analyses in this paper have provided some results which can be used to formulate a conclusion regarding this second hypothesis. The majority of the analyses on country risk in relevant countries and multiple time periods of implied volatility provided statistically significant evidence that there does indeed exist a relationship between these variables. It should however be noted that this relationship seemed to be different for the different categories of countries relevant to the global crude oil market. Additionally, the relationship also seems to take on different forms depending on the length of the time period over which the implied volatility is measured. One limitation of these findings is the fact that hold-out sample analysis has shown that some of the models estimated in these analyses may not be able to perform well when faced with other sets of data. Thus, these findings may not hold for other sets of data. I conclude that there is statistically significant evidence for the hypothesized relationship between country risk and implied volatility & market uncertainty. However, future research is needed to see whether these findings also hold for other sets of data.

Secondly, analyses on political risk and multiple time periods of implied volatility were performed. These analyses provided only little evidence for the hypothesized relationship between political risk in the relevant countries and the implied volatility, or market uncertainty, in the global market for crude oil. As such, future research is needed in order to be able to provide a definite conclusion regarding this hypothesized relationship between political risk in these relevant countries and the implied volatility, or market uncertainty, in the global crude oil market.

One final remark on this set of analyses is that there was quite some evidence that would suggest that the nature of the relationship between the categories' CMCRS and IV is not constant for all different time definitions of IV. Additionally, there were quite some results that were difficult to reconcile with theory. These two notions seem to suggest that changes in CMCRS are not identical in nature, impacting the global crude oil market with different time horizons and through different mechanisms. As such, I would urge future research to also investigate the nature of the relationships.

5.2.1 Implications

The evidence for a relationship between country and political risk, the price of crude oil, and the implied volatility in the market has some major implications, especially for firms who are dependent on the market for crude oil. These firms could benefit greatly from augmenting their financial forecast models and financial planning with insights on how country and political risk may fluctuate. By doing so, they could attain additional insights into how important market factors might fluctuate in the future as well, such as the price of crude oil, but also the implied volatility and the degree of market uncertainty.

These findings also have significant implications for countries that are reliant on the market for crude oil because of the fact that oil rents may influence a country's financial position. Incorporating country and political risk in their financial forecasting and planning models may yield insights regarding the optimal way of planning the production, consumption, import, and export of crude oil.

6 Discussion

As discussed in the previous section, the research in this paper has found correlation between the country and political risk in countries relevant to the global crude oil market, and the price of crude oil and implied volatility in the crude oil market. However, some further comments regarding potential limitations of the analyses performed, and subsequent results and findings are needed.

6.1 Data

The data that is used in research can greatly influence the findings and conclusions that arise from statistical analyses. Some potential concerns relating to the data used arose during the research in this paper.

6.1.1 Sample on CMCRS and CAPRS

Firstly, the sample size of the data on country and political risk scores could have implications for the research. The set of data on country risk consisted of 121 monthly observations. This number of observations should be sufficient according to the consensus on the bare minimum number of observations for statistical analysis to be viable. On the other hand, the set of data on political risk only consisted of 11 annual observations. This sample size is very small and thus not optimal for performing research. Even though the methodology has tried to account for this potential limitation, it is likely that future research can improve greatly on this potential limitation. This could be done by employing a larger sample size, which in turn would improve the statistical power of the analysis, and thus the ability to reveal statistically significant relationships in the data. This could be done by using data with a daily frequency.

6.1.2 Incomplete country imports data

Additionally, there were some mismatches between the different data sources. Some values on the number of oil imports per country were incomplete, thus hampering the validity of the data sources. The countries for which some numbers of oil imports were not included in the data set (China and India) represent a relatively large number of oil imports, meaning that this data limitation may have significant consequences for the results of the subsequent statistical analyses. A recommendation for any future research would be to select data sets that are valid and complete, thus mitigating the problem of having to come up with other measures to get valid observations from the data set used.

6.1.3 Combination of monthly and annual data sources

Next, in the calculation of the CMCRS for the OPEC, OPEC+, non-OPEC importers, and non-OPEC exporters subcategories I made use of annual crude oil production data per country. However, since the data on country risk scores was of a monthly frequency, the consistency of the data set could be Improved by instead making use of a data set with monthly observations on each country's monthly crude oil production.

6.2 Methodology

Besides the data used, the methodology that is employed within research also has major impact on the ability to make valid conclusions regarding hypothesized relationships between variables in the data used. During the performing of the research, some potential limitations to the methodology arose.

6.2.1 Augmenting the GARCH model for estimation of crude oil price

Firstly, the hold-out sample analysis performed in this paper showed that in some cases there was some discrepancy between the model-estimated values and the actual values of the dependent variables over the length of the hold-out time window. This provides evidence for the notion that these estimated models would not perform well when faced with new sets of data. As such, future research could improve on this by augmenting the GARCH model so that it performs better when faced with new sets of data.

After analyzing the data set, an interesting feature in the time series of the variable *price* was found. Looking at the time series shows a large drop in the variable *price* near the end of the year 2014 and the start of the year 2015, after which *price* remains relatively constant, until a large increase in *price* in the year 2021. Following this phenomenon, I have attempted to identify a major underlying factor that may have contributed to these large price movements. As such, I hypothesize that these large fluctuations in *price* are likely caused by the so-called oversupply of crude oil in the global crude oil market. This phenomenon of oversupply causing the severe decrease in the price per barrel of crude oil at the start of 2015 has been alluded to by (Stocker, Baffes, & Vorisek, 2018; Demirbas, Omar Al-Sasi, & Nizami, 2017). Moreover, (Friedman, 2015) has specifically related this specific phenomenon of oversupply to increased supply by the United States of America, mentioning the "surging U.S. production" as a main contributor to sending the global oil market into a state of oversupply around this time. Then, in the year 2021 there came an end to the state of oversupply in the crude oil market, causing crude oil prices to rally in that year (Meredith, 2021), with Resnick-ault (2021) relating this to massive production cuts by the OPEC. As such, improvement on the model could potentially be incorporated by also incorporating a variable capturing oversupply in the crude oil market. However, it is likely that the potential for improvement is not limited to just this variable, meaning that future research could also look into including other relevant variables that will improve the model's performance.

6.2.2 The subcategories

Secondly, the size and definition of the subcategories as employed in this paper may be improved upon. In the determination of the subcategory sizes for non-OPEC exporters and non-OPEC importers I have arbitrarily opted for a size of the top 10 countries per subcategory, as ranked by their average annual crude oil imports and exports. However, this may not be the optimal subcategory size for determining statistically significant relationships. As such, I would recommend future research to come up with a better, less arbitrary methodology for selecting the size and definition of these subcategories.

6.2.3 Theil-Sen estimator

Thirdly, for the analysis on the independent variable CAPRS and all dependent variables, I have opted to employ the non-parametric Theil-Sen estimator methodology in order to investigate the hypothesized linear relationships between these variables. However, the Theil-Sen estimator only found very little statistically significant evidence for such relationships in only a few of the iterations of this statistical analysis. Since there were multiple analyses conducted, it could also very well be the case that this statistically significant evidence was reported due to coincidence. While theory would suggest that the effect of country risk and political risk on the dependent variables in this paper would not be wildly different from one another (particularly due to the interrelatedness of the two concepts as discussed in section 1), it could be the case that there is, in fact, a statistically significant relationship between political risk and the dependent variables in this paper. As such, I would like to recommend future research to employ different methodologies of statistical analyses on the hypothesized relationship between political risk and the price of crude oil and the implied volatility in the crude oil market. This would then contribute by seeing whether other methodologies can reveal statistically significant relationships between these variables, or on the other hand by adding weight to the notion that such a relationship does not exist.

6.3 Results

Finally, some considerations regarding the results that were reported from the statistical analyses and the subsequent conclusions need to be mentioned.

6.3.1 Findings dependent on definition of risk

Firstly, it is very important to note that the findings and conclusions in this paper are entirely dependent on the definition of risk. In the case of this paper, this definition is mostly set by the sources of the data sets on country risk and political risk. As such, the conclusions from this paper may not hold in settings where the definition of country or political risk is different from the definitions maintained in this paper. Moreover, since the country and political risk scores as employed within this paper were synthesized from a plethora of third-party data providers with certain weightings applied, the conclusions are also dependent on the specific weighting of these individual risk factors. Therefore, it would be interesting to see whether the findings of this paper would also hold for settings with different definitions of risk, or even entirely different methods of estimating country and political risk. One suggestion for doing so would be by employing Credit Default Swaps (CDS) for the estimation of a country's relative country risk situation, as compared to other relevant countries. By doing so, CDS rates could provide an alternative proxy for country risk, and perhaps even political risk by employing appropriate methodology.

6.3.2 Reverse causality

Secondly, the concern of reverse causality should be considered. The results of the Granger causality testing revealed that there was some evidence for reverse Granger causality in the sample used in this paper. The evidence, however, was not of such size and frequency that it should significantly limit the findings and conclusions of this paper. It should nevertheless be considered as a potential limitation in future research, and perhaps future research could even look into the causal dynamics between these variables.

6.3.3 Large dependence on USA

Thirdly, regarding the results of this paper, it should be noted that the findings are quite significantly dependent on the inclusion of the USA in the subcategories of non-OPEC importers and non-OPEC exporters. Sensitivity analysis has shown that the results of the analyses change quite significantly when the USA is excluded from these categories. Even though the inclusion of the USA in these categories is within the aim of this paper, it should be a consideration when interpreting, or even applying the findings from this paper.

6.4 Future research

Opportunities for follow-up research are bountiful within this specific direction. As mentioned previously, the results seem to suggest that the relationship between CMCRS and implied volatility with multiple time definitions is not unchanging over time, and potentially also that shocks in CMCRSs can be driven by different drivers with different degrees of impact on the global crude oil market. As such, future research could expand on the knowledge in this field by creating distinctions between drivers of changes in country and political risk and their effects on the global crude oil market. Furthermore, adding the distinction between the spectrum of time definitions of implied volatility could also yield more insight into how the market perceives changes in country and political risk to affect the global crude oil market over time.

Moreover, future research could investigate whether the discovered effects also hold for the options markets for other types of oil, such as Brent or WTI oil. Moreover, future research could also investigate market uncertainty by employing futures contracts instead of options contracts, or by employing other measures. The set-up of this paper could also be applied to other types of commodity markets, in order to contribute to an overview on how country and political risk in relevant countries influence important commodity market variables, and how this influence may differ for different commodities.

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Appendix

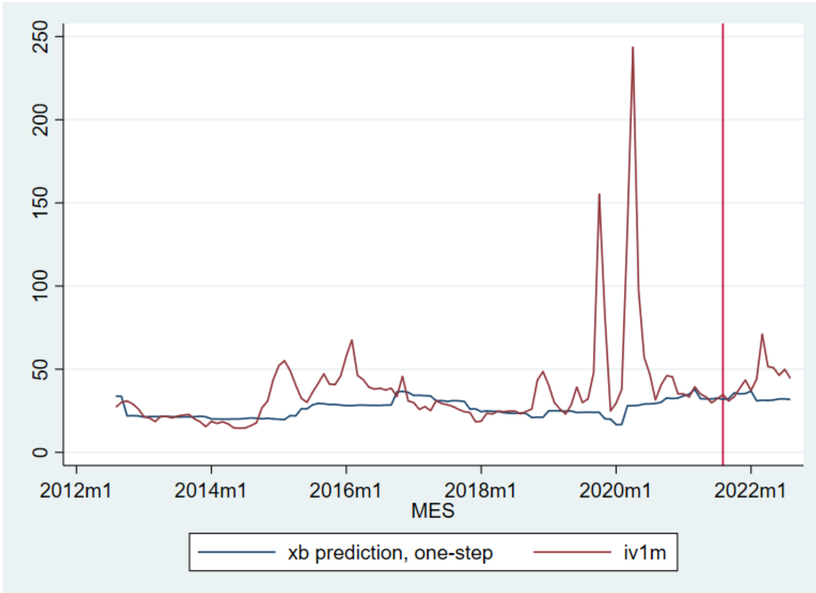

Figure 3: Model-predicted (*xb prediction*) and actual values for *IV1M*

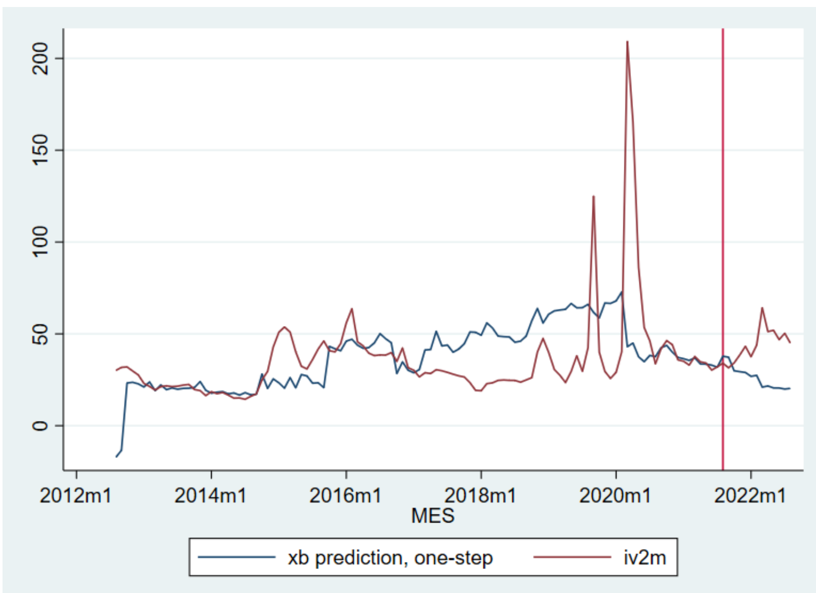

Figure 4: Model-predicted (*xb prediction*) and actual values for *IV2M*

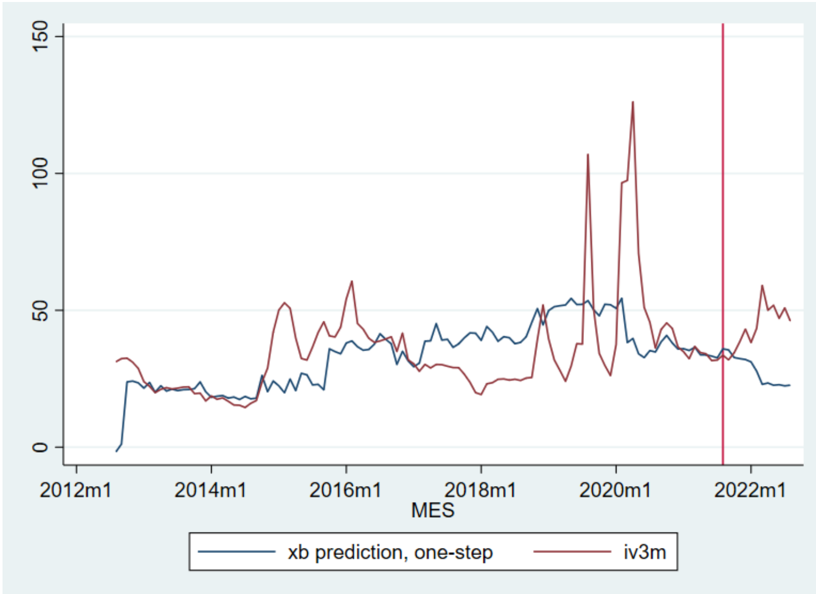

Figure 5: Model-predicted (*xb prediction*) and actual values for *IV3M*

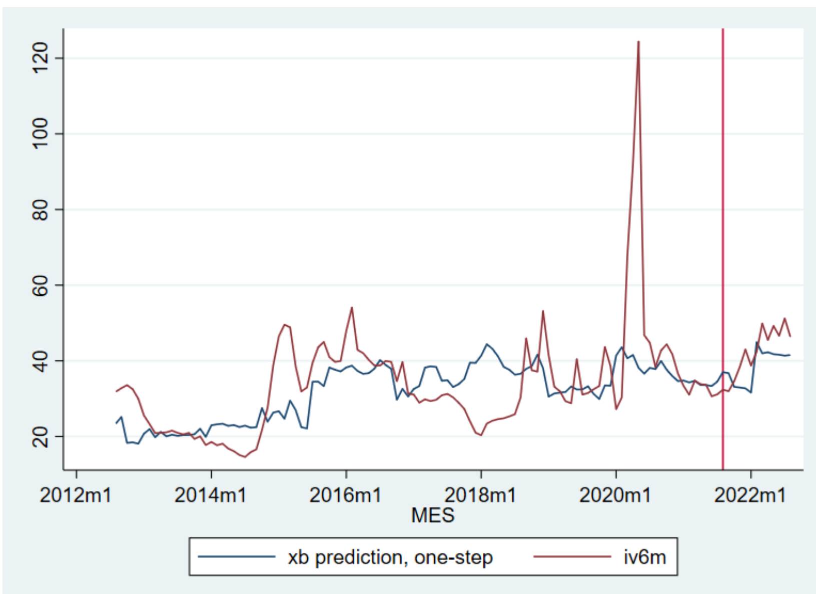

Figure 6: Model-predicted (*xb prediction*) and actual values for *IV6M*

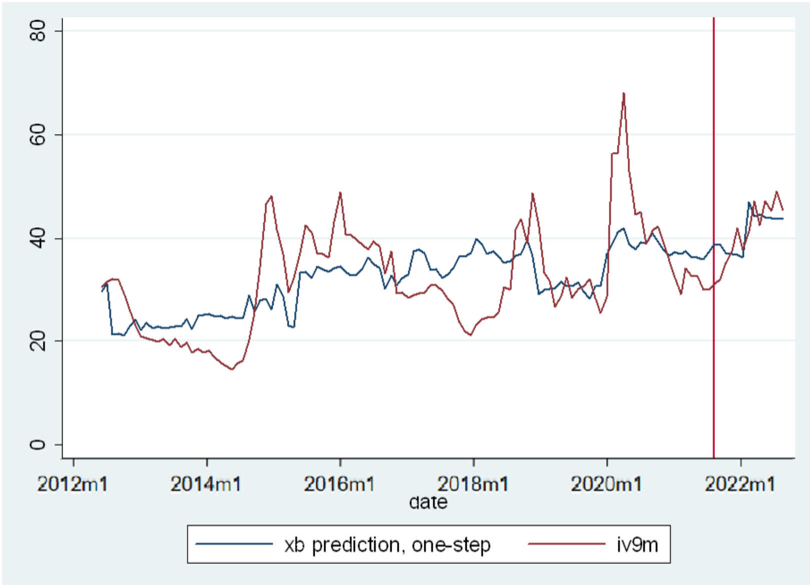

Figure 7: Model-predicted (*xb prediction*) and actual values for *IV9M*

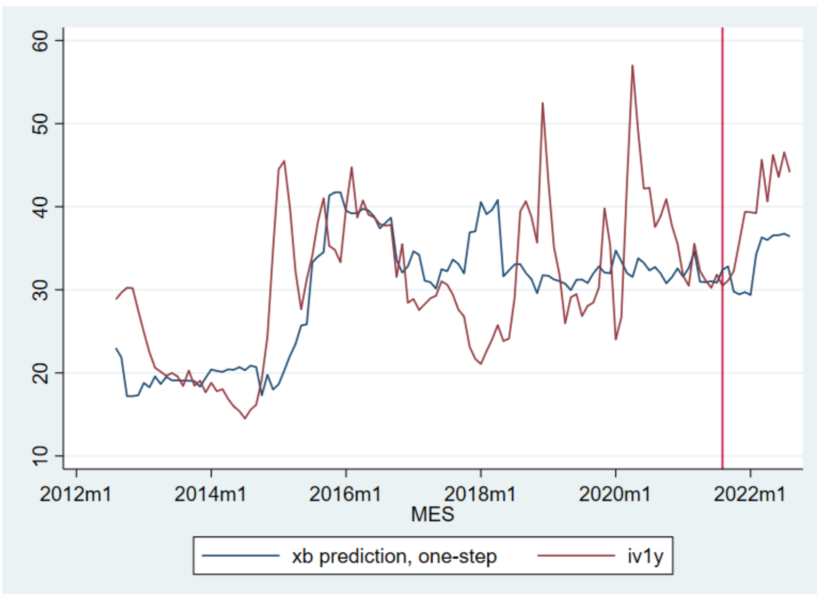

Figure 8: Model-predicted (*xb prediction*) and actual values for *IV1Y*

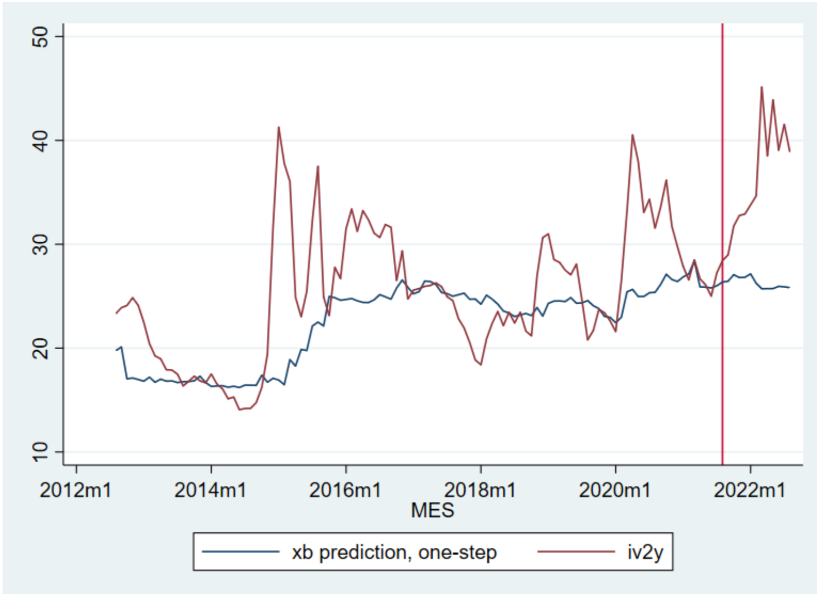

Figure 9: Model-predicted (*xb prediction*) and actual values for *IV2Y*

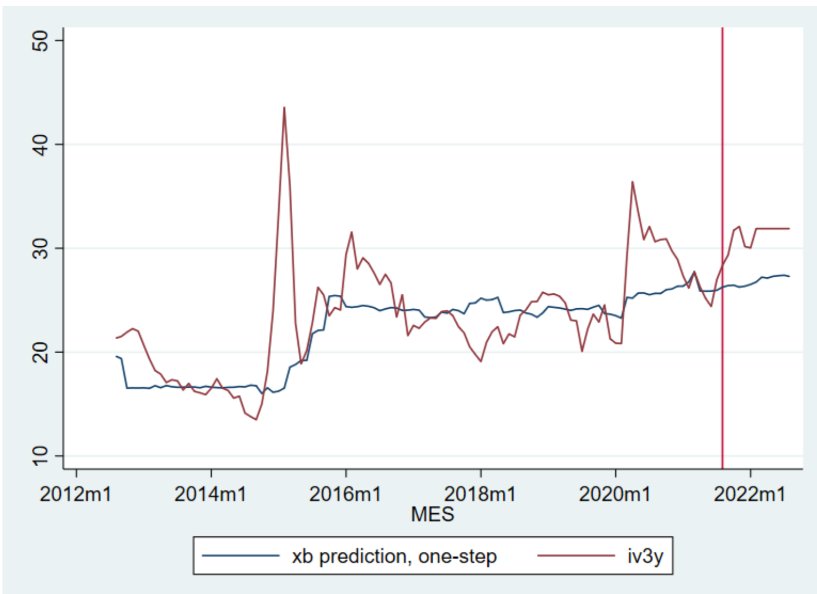

Figure 10: Model-predicted (*xb prediction*) and actual values for *IV3Y*

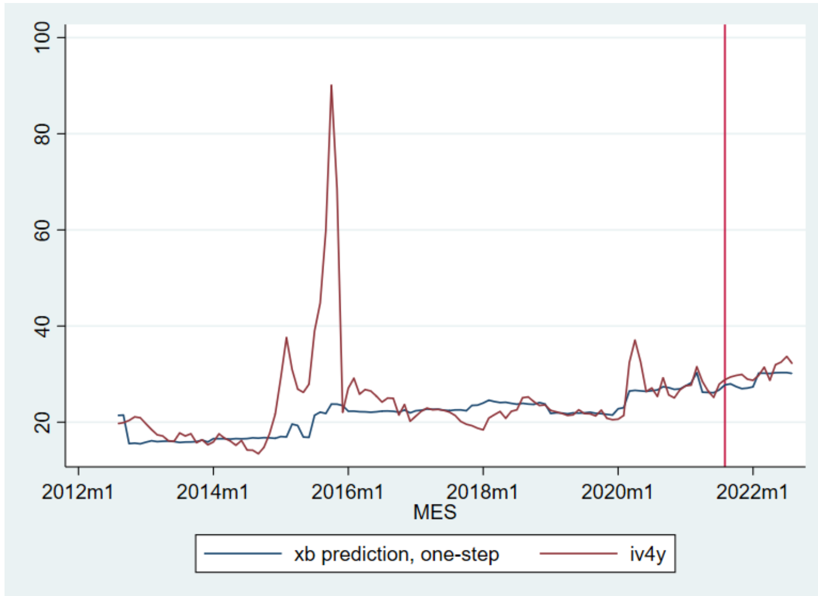

Figure 11: Model-predicted (*xb prediction*) and actual values for *IV4Y*

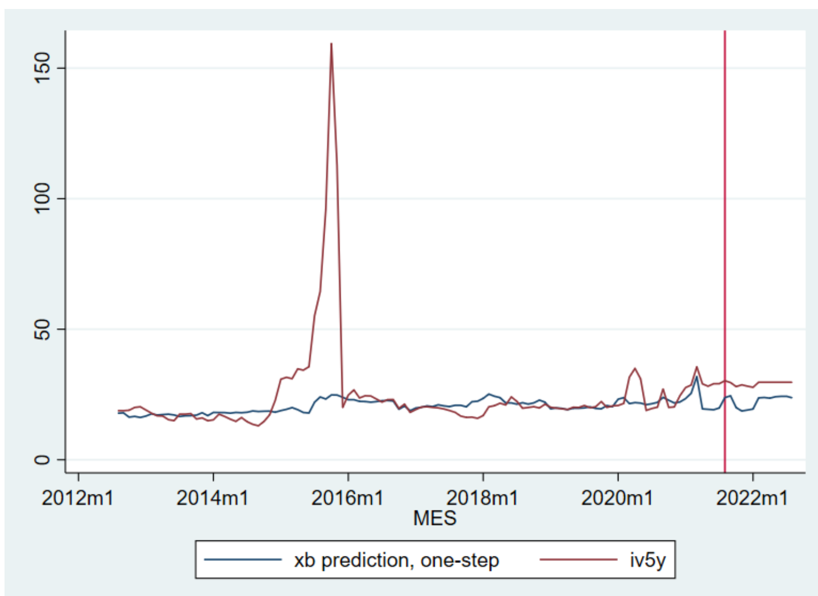

Figure 12: Model-predicted (*xb prediction*) and actual values for *IV5Y*