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**UNCERTAINTY AS A DRIVING FORCE BEHIND THE
CONNECTEDNESS OF OIL-SHOCKS AND TERM
STRUCTURES - EMPIRICAL EVIDENCE FROM
OIL-EXPORTING AND OIL-IMPORTING COUNTRIES**

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Abstract

This paper examines the dynamic effect of oil price shocks on sovereign yield curves, and then analyzes the effect of evolutions in economic policy uncertainty and geopolitical risk uncertainty on the strength of the relationship. The analysis is performed on a group of countries, which are divided based on their positions in the oil market. Oil-exporting countries in the sample include Norway, Mexico, Canada, the UK, and Venezuela; while oil-importers are comprised by China, Japan, South-Korea, the US, and Germany.

The main research question is whether the connectedness of the oil market and the yield curve is following a dynamic trajectory instead of a static one, and if so, whether there is a difference depending on the position of the country in the market. Moreover, the effect of EPU and GPU is especially relevant in the 2020s, which have produced responses from both central banks and central budgets, and a return of geopolitical conflicts. Thus, another question is whether the uncertainty regarding economic policy and geopolitical risk impacts the connectedness of oil and term structures.

The results of this paper indicate that the relationship between oil price shocks and yield curves is time-varying, with some difference between oil-exporting and oil-importing countries. Moreover, the periods when the relationship is significant are associated with times of economic or geopolitical uncertainty. I show that uncertainty regarding economic policy, geopolitics, and market volatility are significant determinants of the connectedness between oil and yield curve, and they sometimes explain a significant portion of it.

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1 Introduction

One of the most important and strategic commodities in the world is crude oil. It is an important input of production not only as an energy source, but also as a raw material. Households and companies depend on it, since it is essential for transportation, heating and electricity production. Thus, understanding its relationship to the economy and financial markets is a top priority for decision makers in business and government as well, which indicates the relevance of this paper.

Although many papers in the past did not distinguish between oil price changes, the literature now agrees on the necessity to decompose oil price shocks into supply and demand shocks. It was [Hamilton \(1983\)](#), who first suggested this decomposition, and later, [Hamilton \(2003\)](#) concluded that the psychological impact of exogenous supply disruptions on policy and consumption may be more important than the actual price movements. In his seminal paper, [Kilian \(2009\)](#) decomposed the oil price into supply, demand and precautionary demand (also known as oil-specific demand or risk) shocks. His results indicated that supply and demand shocks were responsible for only 4% of the variation in monthly oil price. On the other hand, precautionary demand shocks were responsible for 77%. In a later study, [Ready \(2018\)](#) uses daily data of the change in oil price, the returns on a portfolio of oil producer companies and the VIX index, and finds that the majority of the variation of oil price is attributable to supply shocks, with demand playing a much less significant role. [Ready \(2018\)](#) overcomes several weaknesses of the method proposed by [Kilian \(2009\)](#), such as giving too much significance to precautionary demand shocks and being applicable only to monthly data. Thus, this paper is based on the oil price shock decomposition of [Ready \(2018\)](#).

Previous literature has extensively studied the impact of oil price shocks on financial markets, however it has focused more on equities than on the fixed income market. Studies not considering the decomposition of oil price shocks find mixed results, ranging from a positive effect ([Boyer & Filion, 2007](#); [El-Sharif et al., 2005](#); [Mohanty et al., 2011](#); [Sadorsky, 2001](#)), through negative effect ([Ciner, 2001](#); [2013](#); [Nandha & Faff, 2008](#); [Papapetrou, 2001](#); [Sadorsky, 1999](#)) to insignificant effect ([Chen et al., 1986](#); [Huang et al., 2006](#)). In light of these conflicting results, [Kilian \(2009\)](#) and [Kilian and Park \(2009\)](#) propose distinguishing between oil price shocks of different nature. [Kilian and Park \(2009\)](#) show that making a distinction between oil price shocks matters, as supply shocks are less important than aggregate demand or precautionary demand shocks. Later studies based on this methodology largely confirm these findings in that the reaction of equity prices to oil price shocks depend on the nature of the shock ([Aper-](#)

gis & Miller, 2009; Basher et al., 2012; Filis et al., 2011; Wang et al., 2013). On the other hand, Ready (2018) finds a positive correlation between demand shocks and market returns and economic output, while the correlation is negative with supply shocks, which is strongest for industries producing consumer goods. More recently, Clements et al. (2019) studied the effect of oil price shocks on US equities using the decomposition method proposed by Ready (2018), and also introducing two modified versions of it. They found that aggregate demand shocks are the most important ones among the identified shocks, while supply and oil-specific demand shocks are much less relevant. It has also been shown that the modified schemes attribute twice as much explanatory power to aggregate demand shocks as in the baseline specification.

In terms of bonds, the evidence is more limited. Most studies find that the effect of oil shocks on sovereign bond returns and yield curves is dependent on the country (Bernanke et al., 1997; Demirer et al., 2020; Ioannidis & Ka, 2018). Especially, Ioannidis and Ka (2018) consider the whole term structure of two oil-exporting and two oil-importing countries and find that there are some similarities between countries in the same position. However, the authors use a static model for the sample period and use the decomposition technique of Kilian (2009), which can only be carried out on monthly data and has several drawbacks to the method of Ready (2018). This gap has been filled by Umar et al. (2022), who finds that oil demand shocks, risk shocks and U.S. yield curve factors are the main transmitters of spillovers, while Japan, Korea and Brazil are the main recipients. Cepni et al. (2022) using a sample of 19 emerging market economies find that risk shocks put on all three yield curve factors, while supply shocks cause a more significant rise in the rates of oil-importing countries and demand shocks have an upward pressure on level in oil-importing countries.

Another strand of literature has been studying the role of uncertainty in the economy, and its role as a driver of spillovers between markets. Uncertainty has a multi-faceted impact on economic activity, disrupting investments, capital flows, productivity and employment (Bloom, 2009; Converse, 2018; Handley & Limão, 2015; Jurado et al., 2015; Rodrik, 1991). Some evidence suggests that uncertainty regarding monetary policy can have cross-market implications, and act as a major driver of a global financial cycle (Nier et al., 2014; Passari & Rey, 2015; Rey, 2015; 2016). Since oil is a strategic commodity, which many politically faulty countries are involved with, it is also fair to assume that geopolitical risk uncertainty can have an impact on the oil market. Moreover, we can raise the question of whether these uncertainties have an impact on the spillover between oil and financial markets.

The effect of uncertainty can be felt in financial markets, including equities (Arouri et al., 2016; Arouri & Roubaud, 2016; Chang et al., 2015; Hoque & Zaidi, 2020; Liu et al., 2017; Pástor & Veronesi, 2012), fixed income securities (Wisniewski & Lambe, 2015) and oil (Antonakakis et al., 2014). There is also evidence for uncertainty having an impact on the spillovers between two markets, with papers mostly focusing on how economic policy uncertainty and geopolitical risk impacts the spillovers between oil and financial markets (Albulescu et al., 2019; Antonakakis et al., 2017; Arouri et al., 2014; Badshah et al., 2019; Fasanya et al., 2021; Hoque et al., 2019; Lee et al., 2021; Mokni et al., 2021; Mokni et al., 2020; Oliyide et al.,

2021). Despite this rather significant body of research, the role of uncertainty as a driver of oil shock and yield curve connectedness is unexplored.

The contribution of this paper to the literature is fourfold. First, I use the oil shock decomposition of Ready (2018) instead of Kilian (2009) and thus the analysis will be carried out on daily data. Second, I will study the effect of the decomposed oil price shocks on the yield curve in a dynamic framework, which allows me to analyze how the impact and significance of oil price shocks evolved over time. Third, I am extending the analysis to five oil-exporting and five oil-importing countries. Last, I am adding to the uncertainty literature by looking at how uncertainty, especially economic policy uncertainty and geopolitical risk uncertainty and the VIX index have an impact on the relatedness of oil price shocks and yield curves.

In terms of the static analysis, we can observe significant coefficients in the case of demand shocks, but overall this part of the analysis seems to indicate that oil price shocks have little effect on the yield curve. However, the dynamic analysis reveals that the evolution of these coefficients is time-varying and their value is significant around uncertainty episodes. In the second part of the analysis, I find that all three indices involved have significant effects on the time-varying coefficients, and in some cases they explain a significant portion of the variation. The differences are minimal between country groups, although GPR seems to be a relatively more important factor for oil-exporters than for oil-importers.

The rest of the paper is organized as follows: A literature review is presented in Section [2]. Section [3] provides an overview of the methodology, including the Nelson-Siegel yield curve model, the oil shock decomposition and the regression models to study the time-varying impact of oil shocks on the yield curve, and uncertainty's impact on this relationship. Section [4] introduces the underlying dataset. Section [5] discusses empirical results on how the decomposed oil price shocks and the yield curves are related. Section [6] discusses the results regarding the impact of uncertainty indices on the connectedness of oil shocks and yield curves. Finally, Section [7] concludes.

2 Literature review

2.1 Identification of oil price shocks

In the early macro-finance literature, changes in oil prices have been treated homogeneously. It was [Hamilton \(1983\)](#) who first raised the attention to considering oil supply and demand shocks separately. His paper was examining why seven of the eight postwar recessions in the U.S. have been preceded by an increase in the price of oil. He finds that this is not a statistical coincidence and that it is unlikely that there is a third variable driving both oil prices and output. He remarks that neither the demand-oriented approach of the fifties and sixties, nor the supply-oriented approach of the seventies should be abandoned, but rather we should find a way to connect them. In a later study [Hamilton \(2003\)](#) extends [Hamilton \(1983\)](#) by concluding that the relationship between oil prices and GDP growth is nonlinear. He finds that oil price increases are much more important than decreases, and increases have less predictive power if they follow a decrease. He argues that the reason for this relationship is the disruption to investment and consumption caused by the oil price shock, and to test that he isolates exogenous oil price movements using disruptions to the global oil supply. In conclusion, he notes that oil price shocks are not only caused by disruptions, but they may also be precautionary that are driven by concerns regarding future oil supply.

Most of the literature considering oil price shocks as heterogenous follow [Kilian \(2009\)](#). [Kilian \(2009\)](#) takes an index of dry bulk cargo freight rates as a proxy to real economic activity. The logic behind this is that world economic activity is an important determinant of demand for transport services, and freight rates can correlate to this activity. In the shipping market, when demand is increasing, but there is free capacity, or the capacity can be restructured, the supply curve is relatively flat ([Stopford, 1997](#)). On the other hand, when capacities are full, the supply curve is almost vertical, as shipping companies cannot increase their capacities immediately. As there is a lag between the increase in demand for freight capacity and companies purchasing the necessary vehicles to cover that demand, the price of freight rates is expected to increase during high-activity periods. When extra capacity is released, the boom it was originally meant to cover may be gone, causing freight rates to drop. Thus, [Kilian \(2009\)](#) constructs an index as an equally-weighted average of the monthly returns of freight rates on grain, oilseeds, coal, iron ore, fertilizer, and scrap metal. He uses this index along with the monthly change in global crude oil production and the monthly change in the real oil price to decompose the oil price shocks. The decomposition defines an oil supply shock as the percent change in global

crude oil production, and also determines that real economic activity is impacted by supply and aggregate demand shocks. Finally, the change in oil price is affected by all three shocks, leaving oil-specific demand shocks as the residual. The empirical results indicate that supply and aggregate demand shocks only account for about 4% of the variation in the oil price, while oil-specific demand shocks come in at a much more significant 77%. According to [Kilian \(2009\)](#), disruptions of crude oil production play a much less important role, even in the case of geopolitical conflicts, when the increase in oil price is rather attributable to the increased precautionary demand for oil triggered by increased uncertainty rather than the physical supply disruption. Most recently, [Kim and Vera \(2019\)](#) revisited the findings of [Kilian \(2009\)](#) to include to post-financial crisis period. They find that post-crisis oil price changes were mostly driven by aggregate demand shocks and to a lesser extent precautionary demand shocks.

Recently, [Ready \(2018\)](#) proposed an alternative way to decompose oil price shocks, which has a big advantage of being applicable to daily data, allowing for more granular analysis. The approach is based on an intuition regarding the impact of different kinds of oil price shocks on the returns of oil producers. [Ready \(2018\)](#) argues that, whenever an increase in the oil price occurs, oil-producing companies are selling at higher prices, which in turn increase their profits and the value of their equity. However, in case of a supply shock, oil companies sell less in quantity, but at higher prices, leaving their profits by and large unaffected. [Ready \(2018\)](#) thus claims that oil-producing companies hold a natural hedge against supply shocks, while they are positively exposed to demand shocks. [Ready \(2018\)](#) defines shocks to the VIX as a proxy of risk shocks, the returns on the portfolio of oil-producing companies are influenced by both aggregate demand and risk shocks, while supply shocks are determined as the residual. Interestingly, he finds that 78% of the variance in oil prices is explained by supply shocks, 21% by aggregate demand shocks and shocks to the VIX are only responsible for 1% of the variance.

Thus, it seems that there is no consensus between the findings of [Kilian \(2009\)](#) and [Ready \(2018\)](#), as in both cases the residual is responsible for the majority of the variance, but their definition differs. [Demirer et al. \(2020\)](#) notes that [Ready \(2018\)](#) confirms earlier results showing that oil supply shocks have a weaker effect on stock market returns while overcoming the limitations of [Kilian \(2009\)](#) by using daily data and not attributing too much weight to precautionary demand shocks to the detriment of supply shocks. For this reason, this paper uses the identification scheme proposed by [Ready \(2018\)](#).

2.2 Modeling yield curves

In the last 45 years, the finance literature has developed various ways to model and forecast yield curves. In this subsection, I am to provide an overview of these methods.

Two popular approaches include the no-arbitrage approach and the equilibrium approach. The arbitrage-free approach focuses on fitting the yield curve in a way that no arbitrage opportunities exist, an important condition of derivative pricing; whereas equilibrium models focus on modeling the instantaneous rate to construct yields at other maturities. In a seminal paper,

Vasicek (1977) derives a model for the term structure using an arbitrage argument similar to that of Black and Scholes (1973). Vasicek (1977) argues that the return of any bond over the instantaneous rate is proportional to its standard deviation. To conclude, he assumes that the instantaneous rate follows a diffusion process, the price of a discount bond depends only on the instantaneous rate, and that markets are efficient. Cox et al. (1985) develop an intertemporal general equilibrium model, which considers anticipations, risk aversion, investment alternatives, and preferences about the timing of consumption. They argue that the model presented is consistent with the theory of maximizing behavior and rational expectations. Building on Vasicek (1977) and Cox et al. (1985), Hull and White (1990) extends one-state-variable interest rate models. Their modified model is consistent with both the current term structure and either the current volatilities of all spot interest rates or all forward rates. Heath et al. (1992) provide a stochastic model of the term structure, taking as given an initial forward rate curve and potential stochastic processes for subsequent movements. The family of stochastic processes is then restricted by a no-arbitrage condition. Finally, Duffie and Kan (1996) present an arbitrage-free multifactor model of the yield curve. Their model yields at fixed maturities by a multivariate Markov diffusion process.

The main issues related to the no-arbitrage tradition are that it does not take the dynamics of the yield curve into account, since it is mostly focusing on fitting the term structure at a specific point in time. Moreover, it does not provide intuition regarding the macro forces driving the underlying, mostly unobservable factors of the yield curve. On the other hand, equilibrium models do capture dynamics, but are only driven by the short end of the yield curve. They also perform poorly when it comes to out-of-sample forecasting.

To mitigate these shortcomings, many models consider macroeconomic variables as explanatory forces instead of unobservable factors. Ang and Piazzesi (2003) developed a no-arbitrage VAR model that incorporates inflation and economic growth, as well as latent yield factors. It is assumed in the model that the short rate is an affine function of the state variables, the vector of which follows a first-order Gaussian VAR. They found that forecasting performance improves when a no-arbitrage restriction is imposed, and they also concluded that models incorporating macro factors performed better than those with unobservable factors. They showed that macro-factors explain 85% of the variation in bond yields, but this explanatory power is stronger on the short end and the middle of the term structure, whereas on the long end, mostly unobservable factors drive the movement. This finding is consistent with Taylor (1993), whose tradition focuses on a limited number of macroeconomic aggregates (output, inflation) as determinants of the movement of the short rate.

In the following years, the literature began to look for more evidence to find the link between macroeconomic variables and the yield curve. For example, Diebold et al. (2006) and Ang et al. (2007) allow for feedback between macroeconomic and yield factors. Diebold et al. (2006) estimate a model of the yield curve using both latent factors (level, slope, and curvature), while also incorporating macroeconomic variables (real activity, inflation, and the monetary policy instrument), and find strong evidence of a bidirectional effect between macro and latent yield

factors. [Ang et al. \(2007\)](#) find that it is the short end of the yield curve that has the most predictive power when it comes to forecasting inflation. However, they find that overall no-arbitrage yield curve models provide little advantage over simple time-series models in inflation forecasting. [Rudebusch and Wu \(2008\)](#) develop a model combining an affine no-arbitrage model of the term structure with macroeconomic variables for output and inflation. They find that the term structure model developed under the no-arbitrage tradition has macroeconomic variables as significant drivers. They did not find evidence of a slow partial adjustment of the central bank policy rate. Moreover, they also interpret latent factors of the yield curve as macroeconomic variables. For example, the level of the yield curve can be interpreted as a medium-term inflation target and the slope is related to the central bank's stabilization policy. Finally, they find that macro and latent yield factors are both important drivers of the yield curve.

Based on the term structure model of [Nelson and Siegel \(1987\)](#), another strand of the literature focuses on dynamic factor models. In particular, [Diebold and Li \(2006\)](#) take the Nelson-Siegel functional form and modify the framework, so that the resulting dynamic parameters can be interpreted as latent yield curve factors. The authors compare the modified Nelson-Siegel functional form with ten competitor methods for out-of-sample forecasting. For the 1-month horizon, the model is only slightly better than the random walk, as the forecast errors are correlated and the difference between the RMSE of the model and the random walk is insignificant. However, the model's forecast accuracy improves significantly for the 6-month and 12-month horizons. This is consistent with previous literature arguing that canonical affine no-arbitrage models suffer from empirical performance, especially in terms of out-of-sample predictability ([Duffee, 2002](#)). Building on the framework developed by [Diebold and Li \(2006\)](#) and extending it into the macro-finance domain, [Afonso and Martins \(2012\)](#) studies the relationship between fiscal behavior and the yield curve in the US and Germany. They find that fiscal shocks generate responses of the short end of the term structure, while in Germany, fiscal shocks have no significant impact.

In this paper, the Nelson-Siegel function form presented by [Diebold and Li \(2006\)](#) is used for the empirical analysis.

2.3 Oil's impact on financial markets, and why oil shock identification matters

Most of the previous literature focuses on the relationship between equity markets and oil. Initially, the macro finance literature did not consider distinguishing between oil price shocks, thus treating them the same. The result of this was that papers found contradicting, or insignificant effect of oil price shocks on financial markets. [Chen et al. \(1986\)](#) use a factor model to identify how certain economic variables, such as growth, expected and unexpected inflation, interest rates and oil prices. They note that although oil prices are often considered as important factor in asset pricing, they find insignificant oil betas in the whole period and two of the four subperiods considered. Moreover, the risk associated with oil price changes was not priced in

the stock market during the 1968-1977 subperiod, a time when the OPEC cartel became important. [Huang et al. \(2006\)](#) use VAR model estimates on the time series of the S&P 500, 12 major industry stock price indices, 3 individual oil company indices and oil futures traded on the New York Mercantile Exchange (NYMEX) to find return and volatility spillovers. They find that oil price changes only have a significant impact on the petroleum industry index and three oil company stocks. Additionally, the return volatility spillover from oil futures to oil company stocks is even less significant.

Other papers that did not apply a decomposition found a positive effect. [Boyer and Filion \(2007\)](#) analyzes the determinants of Canadian oil and gas companies' stock returns and finds that these returns are positively correlated with appreciations of crude oil. [Sadorsky \(2001\)](#) also studied the return of Canadian oil and gas companies but using a multifactor model that incorporated crude oil prices as well. Results showed that oil has a large and significant impact on equity returns in the sector, increasing stock prices. [El-Sharif et al. \(2005\)](#) focus on the equity market of the United Kingdom and shows that the relationship between crude oil prices and returns is always positive, and mostly significant during the study period. [Mohanty et al. \(2011\)](#) assessed the relationship between oil prices and equity returns in Gulf Cooperation Council (GCC) countries, showing that, with the exception of Kuwait, GCC countries have a positive correlation with oil price shocks. They also found evidence for oil price changes having an asymmetric effect on the equity market.

Finally, several studies reported a negative effect of crude oil on stock markets. [Nandha and Faff \(2008\)](#) analyzed 35 industry indices to provide evidence for the adverse effect crude oil has on equity returns. Their finding suggests that increases in the price of oil have a negative impact on equity returns for all industries, except for mining, oil and gas. They also did not report any asymmetry between the two markets. [Ciner \(2001\)](#) examines the dynamic linkages between oil prices and the U.S. stock market, using the S&P 500 as a proxy. He uses nonlinear casualty tests to find evidence for a relationship between the two markets. The study reports that oil shocks affect stock returns are related in a nonlinear way. [Ciner \(2013\)](#) extends these findings using frequency domain methods, showing that oil price shocks with less than 12-month persistence have a negative impact on stock returns. However, those between 12 and 36 months can contribute to positive returns. This evidence further supports the finding that the linkage between equity markets and oil markets is asymmetric. [Papapetrou \(2001\)](#) uses a multivariate VAR to uncover the dynamic relationship between oil prices and, among others, equity prices in Greece. Her results suggest that oil prices are negatively related to real stock returns. [Sadorsky \(1999\)](#) shows using a VAR that oil prices depress real stock returns, while oil price volatility has an asymmetric effect.

Papers using the oil price shock decomposition of [Kilian \(2009\)](#) generally conclude that precautionary demand shocks can explain a large portion of stock price variation, while supply shocks are marginally important. [Kilian and Park \(2009\)](#) use data on global oil production, global real activity, the real price of oil and U.S. stock returns to decompose shocks to equities into supply, aggregate demand, oil-specific demand and other shocks using a VAR model.

Looking at the responses of stock returns to the three decomposed oil market shocks they find evidence for equities reacting differently depending on the underlying cause. For example, oil supply shocks do not have a significant effect on cumulative returns, but aggregate demand shocks cause a sustained increase in U.S. equity returns. On the other hand, a precautionary demand shock can have negative equity returns as a consequence. The forecast error variance decomposition shows a negligible short-term effect, but a much more relevant long-term effect, as 22% of the variability in U.S. equity returns is accounted for by the three structural shocks, almost half of which is given by precautionary demand shocks. The findings of [Kilian and Park \(2009\)](#) provided the basis for later studies focusing on the relatedness of oil price shocks and the stock market. [Apergis and Miller \(2009\)](#) investigated how structural oil price shocks affect the stock markets of 8 developed countries. They find that equity returns do not have a large response to oil market shocks, although the effect is significant. Interestingly, the oil-exporter Canada's stock market has a weaker response to precautionary demand shocks than the rest of the countries. [Filis et al. \(2011\)](#) investigate the dynamic correlation between stock markets of oil-importing and oil-exporting countries and oil price shocks, using a DCC-GARCH-GJR approach. They find no difference between oil-exporting and oil-importing countries in terms of time-varying correlation. Results also show that in the case of aggregate demand shocks correlation increased positively, while decreased for precautionary demand shocks. For the lagged correlation they find that oil prices had a negative effect in all stock markets regardless of the origin of the shock. [Basher et al. \(2012\)](#) investigate the relationship between oil prices, exchange rates and emerging market stock prices using a SVAR model, in a dynamic framework. They propose that positive shocks to oil prices tend to decrease emerging market stock returns and USD exchange rates on the short-term. They also find evidence for emerging market stock prices increasing oil prices. [Wang et al. \(2013\)](#) also make a difference between oil-exporting and oil-importing countries in investigating the effects of oil price shocks on stock market returns. In terms of findings, they find evidence for segmenting countries into net exporter and net importer groups, as the magnitude, duration and direction of response is dependent on this, as well as whether the changes in the price of oil are driven by supply or aggregate demand shocks. For example, the effects of precautionary demand shocks on the stock market's of net exporters is much stronger than for net importers.

When it comes to financial markets other than the stock market, the most recent literature has been applying the [Ready \(2018\)](#) way of oil shock decomposition. A large portion of this research has been focusing on precious and industrial metals. [Uddin et al. \(2018\)](#) examine the nonlinear effect of oil price shocks on metal returns using a Markov regime switching method. They find a significant positive impact of both demand and supply shocks, and a negative impact of risk shocks on metal returns. Results do not indicate a strong regime effect in the case of supply and demand shocks, but they find that risk shock's influence is regime dependent. [Mokni et al. \(2020\)](#) study the time-varying connectedness of oil price shocks and the price of gold using a TVP-VAR method, while also looking at whether economic policy uncertainty has an impact on this connectedness. They find a weak dynamic connectedness between oil price shocks and

gold returns, with sudden surges during chaotic periods. According to the findings, oil supply shocks are the dominant transmitters of time-varying spillovers, while demand shocks are net receivers. [Oliyide et al. \(2021\)](#) extend this work by looking at the volatility connectedness dynamics measuring forward and backward-looking spillovers between oil price shocks and the metal market. They find a strong connectedness between oil price shocks and five different metals, also highlighting that all the oil shocks serve as net receivers of volatility spillovers. On the other hand, gold is a net shock receiver, thus the authors conclude that it is inappropriate to provide diversification benefits for other assets. [Umar et al. \(2021\)](#) document that demand shocks and risk shocks are the dominant transmitters of shocks for precious and industrial metal returns. and that the total return and volatility connectedness is time-varying. [Youssef and Mokni \(2021\)](#) find that the response of gold returns to oil price shocks depends on the forces-driven oil shocks and gold market conditions. The price of gold has a more intensive response to demand shocks than to supply or risk shocks and the connectedness between the two markets is dynamic in sign, magnitude, and significance. Others focused on the relationship between exchange rates and oil price shocks. [Albulescu et al. \(2019\)](#) studies the effect of oil price shocks on commodity currencies (such as the Australian dollar, New Zealand dollar, etc.) and how economic policy uncertainty affects the relationship. They find that oil is generally a net transmitter of shocks to currencies, this is largely concentrated towards Australia and New Zealand, since they are often used in carry trade strategies. [Malik and Umar \(2019\)](#) find that demand and risk shocks significantly contribute to exchange rate variation, while supply shocks do not really have an effect. They also suggest that the connectedness has significantly increased after the global financial crisis. On the other hand, they do not find a volatility connectedness between oil price shocks and exchange rates.

When it comes to the bond market, recent years have produced significant progress. One of the first papers relating oil prices to rates is [Bernanke et al. \(1997\)](#), investigating endogenous monetary policy response to oil price shocks, to find out whether this has been the cause of crisis following them. As a result, they find that a systematic response to the oil price shocks is responsible for these recessions, thus with a different monetary policy action these could have been avoided. [Hamilton and Herrera \(2004\)](#) challenge this conclusion, since they do not believe that the proposed actions could be implemented by the Federal Reserve, and that the effect of oil price shocks is underestimated by [Bernanke et al. \(1997\)](#), as compared to other researchers' results. They also propose alternative lag lengths, which alter the size of the oil price shocks' effect. [Kilian and Lewis \(2011\)](#) also argue that there is no evidence that the monetary policies of the 1970s and 1980s amplified the effect of shocks. Papers that do not decompose oil price shocks nonetheless find significant results. [Tule et al. \(2017\)](#) investigate the volatility spillover in the Nigerian sovereign bond market due to oil price shocks using a VARMA-AGARCH model. They demonstrate a significant cross-market volatility interaction between oil and the sovereign bond market. [Gormus et al. \(2018\)](#) investigate the impact of energy markets, including the crude oil market on the high-yield bond market, testing for price-transmission and volatility transmissions as well. Results suggest that oil and ethanol markets

significantly impact the high-yield bond market, and also provide evidence for a unidirectional volatility transmission from energy markets to high-yield bonds.

Studies exploring how the decomposed oil price shocks have an impact on fixed income markets reveal significant results as well. [Kang et al. \(2014\)](#) apply the oil shock decomposition of [Kilian \(2009\)](#) to study the impact of oil price shocks on aggregate U.S. bond index returns. They find that a positive oil market-specific demand shocks is followed by a significant decrease in bond index returns on an 8-month horizon. Aggregate demand shocks also have a negative effect on bond returns, which becomes larger over 24 months. All in all, the decomposed oil price shocks accounted for 27.1% of the variation in bond returns at a 24-month horizon. [Ioannidis and Ka \(2018\)](#) decompose the yield curves of oil-exporting and oil-importing countries into latent factors using the modified Nelson-Siegel formula proposed by [Diebold and Li \(2006\)](#) and study the impact of oil price shocks on these factors. The oil price shock decomposition follows [Kilian \(2009\)](#). They find that the size and significance of the relationship depends on the underlying oil price shock and the country's dependence on oil. For example, oil-specific demand shocks results in increases of the level factor for oil-importers, while having no effect in oil-exporting countries. There is also evidence that oil supply disruptions have short-lived negative responses to the slope factor in the US and Canada. Overall, supply and demand shocks account for a significant part of the variation in yield factors.

The most recent papers on the oil-fixed income nexus follow the decomposition technique of [Ready \(2018\)](#). [Demirer et al. \(2020\)](#) study the effect of oil price shocks on 35 sovereign bond markets. They show that the effect of oil price shocks extends to the bond market as well, although the effect is heterogeneous, primarily dominated by demand shocks. [Umar et al. \(2022\)](#) analyze the static and dynamic spillovers between sovereign yield curves and oil price shocks, using the methods of [Diebold and Li \(2006\)](#) and [Ready \(2018\)](#). For the dynamic connectedness measure, they use the Diebold-Yilmaz spillover index ([Diebold & Yilmaz, 2009; 2012; Diebold & Yilmaz, 2014](#)). They find that oil demand shocks, risk shocks, and U.S. yield curve factors are the main transmitters of spillovers, while Japan, Korea, and Brazil are the main recipients. There is also a strengthening of the connectedness during turbulent times. [Cepni et al. \(2022\)](#) refine the approach of [Clements et al. \(2019\)](#) for the modified technique of [Ready \(2018\)](#) to study the impact of oil price shocks on the yield curves of 19 emerging market economies. The results indicate that the response of the yield curve is a function of oil dependence. Risk shocks tend to put upward pressure on all three yield curve factors, while supply shocks cause a more significant rise in the rates of oil-importing countries and demand shocks have a persistent upward impact on the level factor in oil importers.

Despite a large body of evidence for dynamic relationships between oil price shocks and other financial markets, such as equities, metals, or exchange rates, most of the analysis has been static on the fixed income domain, with [Umar et al. \(2022\)](#) being the only exception. This paper aims to fill this gap by looking at the contemporaneous relationship between oil price shocks and yield curve factors for a large set of oil-exporting and oil-importing countries.

2.4 Uncertainty and financial markets

Uncertainty regarding economic events and geopolitics has been an important feature of recent years, with notable events including the Great Financial Crisis, trade wars between China and the U.S., the coronavirus pandemic, or the military escalation between Ukraine and Russia. Similar events can have an outside and multi-faceted impact on economic conditions, as it has been shown by numerous papers. [Rodrik \(1991\)](#) shows that increased policy uncertainty can withhold corporate investments until it is resolved. The results indicate that even moderate policy uncertainty can deter investments, thus sometimes even sensible reforms can cause damaging ripple effects due to the surrounding uncertainty. [Converse \(2018\)](#) explored how volatile international capital flows can interact with maturity mismatch of firm balance sheets and increases in the volatility of output, investment, and total factor productivity in emerging countries. Using a model of a small open economy, the results show that firms adjust their long-term investments as a response to uncertainty regarding the availability of foreign borrowings, resulting in fluctuations of investments, output and aggregate productivity. In a seminal paper, [Bloom \(2009\)](#) developed a model which can be used to simulate a macro uncertainty shock, producing a rapid drop and rebound in output and employment, occurring due to uncertainty causing firms to temporarily pause their investments and hiring activity. He shows that there is a good match between the simulated data and VAR estimations on actual data. [Jurado et al. \(2015\)](#), building on previous studies, developed a macroeconomic uncertainty indicator, with significantly different development from traditional proxies, such as stock market volatility. As a contrast to [Bloom \(2009\)](#), who identified 17 major uncertainty dates, [Jurado et al. \(2015\)](#) only uncovered three such events in the identical time window. They argue that this is because there is much predictable volatility, which is incorporated in the traditionally used proxies. [Handley and Limão \(2015\)](#) show using the case of Portugal's accession to the European Community that firms' export investment is lower amid trade policy uncertainty even if tariffs are low. There is also increasing evidence arguing that monetary policy by the U.S. Fed serves as a driver of a global financial cycle ([Nier et al., 2014](#); [Passari & Rey, 2015](#); [Rey, 2015](#); [2016](#)), which implies that U.S. economic policy uncertainty can have ripple effect in the global economy, acting as a driver. In 2016, Mark Carney, the governor of the Bank of England identified three key uncertainties driving economic performance: geopolitical, economic and policy uncertainty ([Carney, 2016](#)).

Due to the importance of uncertainty as a driver of economic activity, many studies attempted to build methods to measure uncertainty. Most recently, [Baker et al. \(2016\)](#) proposed an index to measure economic policy uncertainty (EPU) in the U.S. The index takes the weighted average of news coverage related to policy-related uncertainty, the number of federal tax code provisions set to expire in the future and disagreement among economic forecasters. They found that higher values of the index developed is associated with increased stock price volatility, reduced investment and hiring activity in dependent sectors, such as defense, healthcare, financial services and infrastructure. When it comes to geopolitical risk (GPR), [Caldara and Iacoviello](#)

(2022) developed a widely used index measuring the frequency of articles in leading newspapers related to rising geopolitical tensions. They find that the consequences of high GPR include adverse effect of employment and trade, drops in stock market returns (but with heterogeneous response across sectors), and capital flows from emerging countries to safe havens.

The effect of uncertainty is not limited to the real economy, but it is also quite prominent in the financial markets. [Pástor and Veronesi \(2012\)](#) analyzed the effect of changes in government policy on stock prices with a model featuring uncertainty about government policy. The empirical predictions of this model include that stock prices should fall at the announcement of a policy change, which should be proportional to the previous uncertainty. However, [Chang et al. \(2015\)](#) investigated the causal link between policy uncertainty and stock prices and showed that stock prices do not necessarily fall following an increase in policy uncertainty. [Arouri and Roubaud \(2016\)](#) studied the EPU-stock market nexus for China, India and the U.S., finding that an increase in policy uncertainty in the U.S. and India reduces return and increases volatility, while the contrary is true for China. [Liu et al. \(2017\)](#) show that the impact of EPU has a significant positive effect on future volatility. [Arouri et al. \(2016\)](#) study the impact of EPU on the U.S. stock market over the period 1900-2014 and find that policy uncertainty reduces stock return, this being more persistent during extreme volatility periods. As a proxy to the fixed-income market, [Wisniewski and Lambe \(2015\)](#) examined the link between economic policy uncertainty and changes in CDS spreads. While in Europe the relationship between the two is bidirectional, in the US mostly changes in policy uncertainty led to differences in the CDS index. Economic policy uncertainty is also related to oil price changes, as shown by [Antonakakis et al. \(2014\)](#). EPU responds negatively to aggregate demand shocks, and acts as a transmitter of shocks between 1997 and 2009. However, after 2009 supply-side and precautionary demand shocks are the net transmitters. When it comes to GPR, [Hoque and Zaidi \(2020\)](#) show that the effect of global and country-specific geopolitical risk uncertainty on stock returns in Brazil, India, Indonesia, South Africa and Turkey exhibit nonlinear properties. Geopolitical risk uncertainty can affect equities both positively and negatively depending on contemporaneous time, lag time and volatility regimes. With the exception of India, local uncertainties adversely affect local stock performance.

Empirical evidence also finds an effect of uncertainty on causal relationship in financial markets. [Antonakakis et al. \(2017\)](#) finds that GPR triggers a negative effect on the covariance of oil and the stock market. Using Granger-causality test, [Lee et al. \(2021\)](#) find a unidirectional causality from geopolitical risk to oil price, and a bi-directional causality from oil price to green bonds. There also seems to be a causality from geopolitical risk to green bonds. [Albulescu et al. \(2019\)](#), studied the effect of EPU on the connectedness of the oil market and commodity currencies and found that there is a causal relationship between EPU and the connectedness of oil and currency market, which is passing through oil prices. [Fasanya et al. \(2021\)](#) extend this by examining the same pass-through relationship for global foreign exchange pairs using spillover and nonparametric causality-in-quantiles approaches. They find that spillover for these assets classes is driven by U.S. EPU around the lower and median quantiles. [Arouri et al. \(2014\)](#)

investigated the impact of EPU from major net oil importers on GCC stock markets and find that an increase in EPU has a negative effect on stock returns, which is persistent and interacts with oil price changes. Moreover, EPU also has a delayed, positive effect on volatility. [Badshah et al. \(2019\)](#) extends the analysis to the stock-commodity domain, showing that EPU has a positive, significant effect on stock-commodity correlations, especially for energy and industrial metals. This effect is stronger during weak economic periods. [Hoque et al. \(2019\)](#) examined the effect of GPR, global EPU and oil price shocks for the Malaysian stock market. While GPR has no direct impact on the stock market, there is a significant indirect impact through economic policy uncertainty. On the other hand, EPU has a negative influence on stock markets, magnified by GPR. The impact of oil demand shocks is passed through EPU, while supply shocks are amplified by GPR. There is also evidence for the pass-through of EPU on the connectedness of oil and commodities. [Mokni et al. \(2020\)](#) used the TVP-VAR model inspired by [Diebold and Yilmaz \(2014\)](#) to examine the dynamic connectedness between structural oil price shocks and gold returns and relate this to EPU. The weak connection between oil shocks and gold presents upticks during turmoil, and EPU affects significantly the relationship. [Mokni et al. \(2021\)](#) revisit this topic including other precious metals and investigating the effect of COVID-19. The total spillover index increased widely during the COVID-19 period and shows that gold is still the most dominant "safe-haven" as a hedge against uncertainty. [Oliyide et al. \(2021\)](#) extends [Mokni et al. \(2020\)](#) and find a strong connectedness between four identified oil price shocks and five precious metals. The strong connectedness between oil and precious metals is driven by economic policy uncertainty according to their evidence.

Although economic policy uncertainty and geopolitical risk has been involved in many studies evaluating their effect on causal relationships in financial markets, their effect on the connectedness between oil price shocks and the yield curve is undiscovered, and this paper aims to fill this gap.

3 Methods

3.1 Decomposition of structural oil price shocks

Although a large portion of the literature treats oil price shocks as exogenous and does not distinguish between supply and demand shocks, this paper aims to differentiate between three structural oil price shocks: supply, aggregate demand, and oil-specific demand shocks. This is done using the decomposition technique proposed by [Ready \(2018\)](#).

To disentangle the three structural oil price shocks, data is needed for the change in the oil price, innovations to the returns of oil producing firms and unexpected changes in the discount rate. For the oil price, the closest expiry NYMEX WTI crude oil futures contract at month end is used. For the oil producing firms the monthly returns on the World Integrated Oil and Gas Producers Index are used, which represents a portfolio of large publicly traded oil producing firms, excluding nationalized producers. Finally, for changes in the discount rate, the unexpected changes in the VIX index are used, calculated as residuals to an ARMA(1,1) process.

Define the vector Z_t , which contains the orthogonalized supply shocks (s_t), demand shocks (d_t) and risk shocks (v_t), and the vector X_t which contains the actual data, such as the change in the oil price (Δp_t), the return on the oil producer portfolio (R_t^{Prod}) and the change in the discount rate ($\xi_{VIX,t}$). Matrix A contains the coefficients for the SVAR.

$$Z_t = \begin{bmatrix} s_t \\ d_t \\ v_t \end{bmatrix}; X_t = \begin{bmatrix} \Delta p_t \\ R_t^{Prod} \\ \xi_{VIX,t} \end{bmatrix}; A = \begin{bmatrix} 1 & 1 & 1 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix} \quad (3.1)$$

The matrix A maps the identified oil price shocks into the observable data such that all three oil shocks contribute to the change in the oil price, while the returns on the portfolio of large oil producers is unaffected by supply shocks. Moreover, the changes in the discount rate are only affected by the risk shocks.

$$X_t = AZ_t \quad (3.2)$$

To impose orthogonality on the identified shocks, the following condition should be met:

$$A^{-1} \sum_x (A^{-1})^T = \begin{bmatrix} \sigma_s^2 & 0 & 0 \\ 0 & \sigma_d^2 & 0 \\ 0 & 0 & \sigma_v^2 \end{bmatrix} \quad (3.3)$$

where $\sum_x$ is the covariance matrix of the observable data and σ_s^2 , σ_d^2 , and σ_v^2 are the variances of the identified oil price shocks.

The oil price decomposition is used by several peer studies, including [Demirer et al. \(2020\)](#) and [Umar et al. \(2022\)](#), both of which focused on the relatedness of oil price shocks and sovereign bond yields or yield factors.

3.2 Construction of latent yield factors

Popular theoretical models of the term structure include the no-arbitrage and the equilibrium tradition, but [Diebold and Li \(2006\)](#) for a third approach, which is a modified Nelson-Siegel functional form ([Diebold & Li, 2006](#); [Nelson & Siegel, 1987](#)). The method constructs a time series of three latent factors, which can be interpreted as the level, the slope, and the curvature of the yield curve. The original [Nelson and Siegel \(1987\)](#) functional form, as extended by [Siegel and Nelson \(1988\)](#) is:

$$f_t(\tau) = \beta_{1t} + \beta_{2t}e^{-\lambda_t\tau} + \beta_{3t}\lambda_t e^{-\lambda_t\tau} \quad (3.4)$$

The above equation is working with the forward rate curve. Transforming this to the yield curve, we get

$$y_t(\tau) = \beta_{1t} + \beta_{2t} \left(\frac{1 - e^{-\lambda_t\tau}}{\lambda_t\tau} \right) + \beta_{3t} \left(\frac{1 - e^{-\lambda_t\tau}}{\lambda_t\tau} - e^{-\lambda_t\tau} \right) \quad (3.5)$$

[Diebold and Li \(2006\)](#) and [Ioannidis and Ka \(2018\)](#) interpret the parameters of this equation as latent factors of the yield curve. The variable β_{1t} corresponds to the level of the yield curve at any given time since its loading is 1. and thus, this one is also called as a long-term factor. The loading on β_{2t} as we move further from zero maturity decays monotonically to zero, thus it can be viewed as the short-term factor, or the slope of the yield curve. The loading on β_{3t} starts at zero, increases up to a certain maturity, and then starts decaying again to zero. Thus, this factor is viewed as the medium-term factor, or curvature. The behavior of these loadings is governed by λ_t , an exponential decay rate. Small values of the decay rate produce slow decay, thus giving a better estimate of the yield curve at long maturities, while a higher value causes fast decay, making the estimate for shorter maturities more accurate.

The four parameters could be estimated by nonlinear least squares for each t period however, [Diebold and Li \(2006\)](#) propose fixing the exponential decay term, resulting in a simple ordinary least squares regression for each time period. They argue that λ_t determines the maturity at

which the loading on the curvature factor achieves its maximum. Since two- or three-year maturities usually represent the point where the curvature reaches its maximum, they pick 30 months as the maturity where the medium-term factor reaches its maximum, resulting in $\lambda_t = 0.0609$. Figure [1] represents the loadings with λ_t fixed at 0.0609.

Insert Figure 1 here

Throughout the analysis, the term structure model of [Diebold and Li \(2006\)](#) is used, with the decay term fixed at 0.0609. The aim of fixating the decay term is to keep the identification simpler and more straightforward, while not losing the advantages of the formula, as [Diebold and Li \(2006\)](#) shows. In fact, the proposed yield curve model performs the best for forecasting when compared to several competing methods, even with the fixed decay term.

3.3 Time-varying connectedness of oil price shocks and yield curve factors

The method to find out the relationship between oil price shocks and the identified yield curve factors is inspired by [Demirer et al. \(2020\)](#) and [Mokni \(2020\)](#). Let us define a simple linear equation connecting each yield curve parameter to the structural shocks as follows:

$$\Delta f_{i,t} = \beta_0 + \beta_{SS}SS_t + \beta_{DS}DS_t + \beta_{RS}RS_t \quad (3.6)$$

where f_i is one of the yield curve factors, SS , DS and RS are the structural supply shocks, demand shocks and risk shocks, respectively and β_{SS} , β_{DS} and β_{RS} are the coefficients relating the yield curve factor to the supply, demand and risk shocks, respectively. Estimating the coefficients can tell the sensitivity of each yield curve parameters to the oil price shocks based on a given sample period, however, the aim of this paper is to translate this approach into a time-varying framework. A similar approach is defined by [Mokni \(2020\)](#) for the stock market.

$$\Delta f_{i,t} = \beta_{0,t} + \beta_{SS,t}SS + \beta_{DS,t}DS + \beta_{RS,t}RS \quad (3.7)$$

Thus, each parameter is estimated for a given time t , creating a rolling-windows analysis. In this study, the coefficients are estimated based on one calendar year's data. As a result, we can depict a time series of coefficients to see how these have evolved over time.

3.4 Uncertainty measures and their effect on connectedness

When studying the effect of uncertainty on the time-varying coefficients, three measures are involved: the U.S. EPU index by [Baker et al. \(2016\)](#), the Geopolitical Risk index by [Caldara and Iacoviello \(2022\)](#) and the VIX index as a control variable.

To establish a relationship between the time-varying coefficients and the oil price shocks, the following simple linear equation is used:

$$\beta_{OS_i,t}^{f_j} = \beta_0 + \beta_{EPU}EPU_t + \beta_{GPR}GPR_t + \beta_{VIX}VIX_t \quad (3.8)$$

where $\beta_{OS_i}^{f_j}$ represents the coefficient between oil price shock $i = 1, 2, 3$ and yield curve parameters $j = 1, 2, 3$, EPU, GPR and VIX are the U.S. EPU index, GPR index and VIX index, respectively and β_{EPU} , β_{GPR} and β_{VIX} are the estimated coefficients of the EPU, GPR and VIX index, respectively.

4 Data

The analysis in this paper requires data for the estimation of the yield curve parameters, the identification of structural oil price shocks and the estimation of the uncertainty impact. The time frame of the analysis is from 10/01/2003 to 01/28/2022, with the period between 10/01/2003 to 10/01/2004 only used for the time-varying analysis to estimate the dynamic coefficients for the beginning of the study period.

In terms of the yield curve, data has been gathered for 10 countries, 5 of which have been identified as net oil exporters (Canada, Mexico, Norway, United Kingdom and Venezuela) and the other 5 as net oil importers (China, Germany, Japan, South-Korea and United States). For the study period, yields of 15 maturities (3 and 6 months, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 20 and 30 years) have been used, the summary statistics of which is presented in Table [1]. Having estimated the yield curve factors, these have been scaled 0 to 1 for the time-varying analysis, to make comparability within and across countries and country groups easier. A chart of these rescaled yield curve factors is presented in Figure [2].

Insert Table 1 and Figure 2 here

Generally, emerging economies of our sample, such as Mexico and Venezuela presented the highest and most variable interest rates over the study period, while advanced economies had lower rates. The infamous, close to zero interest rate policy present in Germany and Japan is also well reflected in the summary table. Looking at the evolution of the scaled yield curve factors, we can see a co-movement between the parameters of oil-exporting countries, with Venezuela being a notable exception. While there is also a co-movement between oil-importers' yield curve factors, this is limited to the final years of the sample, and not true for the curvature factor.

For the oil price shock decomposition, I used the the closest expiry NYMEX WTI crude oil futures contract at month end, while for the oil producer's stock price index the MSCI World Energy Index was used. Time series of the VIX index has also been used to proxy the unexpected changes in the discount rate. These have been used to identify the oil price shocks of Ready (2018). The summary statistics are presented in Table [2]. The time series of WTI, the MSCI World Energy Index and the VIX index is presented in Figure [2], while the resulting oil price shocks are presented in Figure [3]. The volatility of oil price changes and returns on the MSCI index had two major episodes during the sample period, one related to the Great Financial Crisis and the other, more recent, to the coronavirus pandemic and the following energy price boom. The unexpected changes in the VIX index did not have major

spikes in volatility during the study period.

Insert Table 2 and Figure 2-3 here

When it comes to the uncertainty indices, the U.S. economic policy uncertainty index of [Baker et al. \(2016\)](#) and the geopolitical risk index of [Caldara and Iacoviello \(2022\)](#) are used at daily frequencies. The evolution of these indices is presented in Figure [2], while the summary statistics of are presented in Table [2]. Both indices are quite volatile as can be seen on the charts and the standard deviations. The U.S. EPU had a spike during the 2007-2009 era surrounding the great financial crisis, and most notable during 2020-2021, due to the high uncertainty related to COVID-19. The GPR had no notable spikes during the study period, and although the recent conflict in Ukraine caused a more sustained increase, this event is not included in the study period.

5 The impact of oil price shocks on the yield curve

In this section the effect of structural oil price shocks on yield curve factors is investigated. First, the static analysis is carried out, as explained by Equation [3.6]. Then, the results of the time-varying analysis described by Equation [3.7] is presented.

5.1 Static analysis

As a starting point, a static analysis of the yield curve - oil price shock connection is carried out. The results are shown in Table [3] for oil-exporting countries and in Table [4] for oil-importing countries. The first general observation we can make is that oil price shocks explain less than one percent of the variation of the yield curve factors, regardless of the country's status. Another general observation is that, with only a few exceptions, the coefficients are insignificant at the usual significance levels.

Taking a closer look at the results of oil-exporting countries, there are a few significant coefficients. In Canada, the effect of demand shocks on the level is positive and significant at 10% while the effect of demand shocks on slope is negative and significant at 10%. In Norway, the case of the level factor is the same as for Canada, while the slope is negatively and significantly affected by demand and risk shocks at 5%. If we ignore the fact that most of the coefficients are insignificant we can make the following general conclusions for oil-exporting countries: (1) the level is usually negatively affected by supply shocks, positively affected by demand shocks and negatively affected by risk shocks; (2) the slope is positively affected by supply shocks, negatively affected by demand shocks, while the effect of risk shocks varies; (3) risk shocks usually have a negative effect on curvature while for supply shocks and demand shocks the effect on curvature varies.

Insert Table 3 here

Focusing on the oil-importing countries, again we can detect some significant coefficients. For China, the effect of demand shocks on slope is significantly negative at the 5% level. For South Korea, the effect of demand shocks on level is significantly positive at 10%. In this case there is no general pattern of the coefficients across the group.

Insert Table 4 here

All in all, most of the significant coefficients are coming from demand shocks, and the only difference between oil-exporting and oil-importing countries seems to be that oil-exporters are

more synchronized in the response of their yield curves, which may be due to the relatively higher importance of the commodity for their economies.

5.2 Dynamic analysis

Although the static analysis implies that oil price shocks have little effect on the yield curve, this result may be biased as it is influenced by the chosen starting and ending dates and the time frame of the regression. Thus, I undertake a time-varying analysis, which is a rolling-window regression of the same model applied in the static analysis. The data used for the estimation of the coefficients is always the previous one calendar year, and the regressions are performed daily.

5.2.1 *Effect on level*

Firstly, we examine the effect of oil price shocks on the level factor. Figure [4] presents the time-varying coefficients for oil-exporting, Figure [5] for oil-importing countries. Table [5] presents summary statistics.

Insert Table 5 here

Starting with oil-exporters, we can see that the effect oil price shocks on level varied over time, with a sustained significant effect in the case of some countries. For example, in Canada we can observe a significantly negative effect of supply shocks around 2008, while around the same period the effect of demand shocks was significantly positive. We can also observe a significantly positive reaction to demand shocks round 2014, while risk shocks had a significantly positive effect at the end of 2019 / beginning of 2020. In Mexico, when the effect of supply shocks was significant, it was always negative, which included the period around 2008 and a longer period around 2020-2021. Demand shocks also played a significant, but negative role in 2008 and 2015. Risk shocks barely had any significant episodes in Mexico, which is surprising considering that it is an emerging economy. Moving on to Norway, we can observe more sustained significant periods only in the case of demand shocks, which was positive around 2014, but turned to negative around 2015. The results are also similar for the U.K., although the magnitude is much higher. When it comes to Venezuela, supply shocks had a long and significant negative effect around 2008-2009, while risk shocks also had a significantly negative effect during the same period. The effect of risk shocks turned positive and significant around 2010 which lasted until the beginning of 2021. In terms of demand shocks, we can observe a significant and positive episode around 2012.

Insert Figure 4 here

On the oil-importers' chart we can also see many periods where the coefficients were significant. For China their distribution is more sporadic, but generally all three shocks played a role around 2008, with supply and risk shocks having a positive and demand shocks having a negative effect. We can also observe a significantly positive period caused by demand shocks.

For Germany, demand shocks had the most sustained effect. Around 2014 demand shocks increased the level significantly, and around 2020 they also had a significant positive effect. Japan is pretty similar in having been affected by demand shocks in 2014, almost to the same extent as Germany, while also documenting a short, but significant positive effect around 2020. Moreover, risk shocks played a significant negative role around 2017-2018. On the charts of South Korea, we can observe a significant negative supply shocks effect around 2008, a significant, positive demand shock effect around 2011 and 2020, and a significant positive risk shock effect in 2020-2021. Finally, in the US we can observe a short positive effect of supply shocks during 2014 and a short, positive effect of demand shocks around 2014 that quickly turned into a more sustained negative period in 2015.

Insert Figure 5 here

As a synthesis of the time-varying coefficients relating oil price shocks to the level factor, we can conclude that the most significant drivers were the demand shocks for both oil-exporting and oil-importing countries during the study period. There is no synchronization of the effect of supply shocks for oil-exporters, while for the demand shocks we can generally see some significant and positive effect around 2014-2015. All in all, risk shocks do not play a significant role in determining the level factor of oil-exporter countries. An exception to these is constituted by Venezuela, where demand shocks had a positive effect on the level around 2011-2012, and risk shocks were also significant. The differentiated behavior is likely to do with Venezuela's unique state system and its reputation with foreign investors.

For oil-importing countries the pattern is similar for the demand shocks, with a positive effect around 2014, complemented by a positive effect around 2020 (which we could not detect for oil-exporters). Supply and risk shocks play a more significant role as well, although their pattern is less synchronized.

5.2.2 *Effect on slope*

Next, we analyze the effect of oil price shocks on the slope parameter. Figure [6] presents the time-varying coefficients for oil-exporting, Figure [7] for oil-importing countries. Table [6] presents summary statistics.

Insert Table 6 here

Firstly, taking a closer look at oil-exporting countries, we can detect that in Canada supply shocks had a significant positive effect on the slope around 2008. This effect can be to some extent detected for all the other oil-exporting countries, except for Venezuela. Moreover, around 2014-2016 we can observe a significant effect of supply shocks, although this was positive for Mexico and Venezuela, while negative for Canada, Norway and the UK. Moving on to the demand shocks, it is again interesting to see that they had a significant effect for more sustained periods. For example, demand shocks had a significant negative effect around 2007 and 2014 in Canada, which around 2015 turned into a positive effect. While significant periods of demand shocks are more sporadic for Mexico, in Norway we can document a significant, negative effect

around 2014 and 2020. Interestingly, the same can be observed for the UK, where the negative effect of 2014 was followed by a longer period of positive effect around 2014. Similar to Mexico, in Venezuela the effect of demand shocks was more sporadic and diverse. Risk shocks do not seem to have a significant and sustained effect on the slope, with the exception of Canada around 2007, and Venezuela, around 2012, both of which were significant and negative effects.

Insert Figure 6 here

Moving on to the oil-importers, at first look we can see that supply shocks are relatively more important for the slope. We can document a more significant effect of supply shocks for Germany and the U.S., as for the former we can observe a positive effect around 2008 and, more sporadically, around 2010, and for the latter we can see a positive effect around 2015. When it comes to the demand shocks, the pattern seems more heterogenous. In China, we can observe a significant and negative effect around 2014, similarly to Germany. In the case of Germany, there was a sustained positive effect period around 2007. In Japan, around 2015 we can document a significant, positive effect, just as for the U.S. In case of South Korea, the only relatively sustained, significant effect was around 2012. Risk shocks seem more insignificant as well. although in China they played a significant, positive role around 2019, a significant and negative one around 2008 for Germany, and a significant negative one for the U.S. around 2020.

Insert Figure 7 here

Summarizing the effect on the slope, the oil-exporting countries seem to be more synchronized, especially in the case of supply shocks. Demand shocks again played a significant role, although their sign was homogenous within the country group. Risk shocks generally were not significant, with some exceptions for Canada and Venezuela. Oil-importing countries were less homogenous in the case of slope. Generally, around 2014 we could document a negative effect, but all in all countries within this group walked their own path. In case of the oil-importers, demand shocks played a significant role, although with less synchronization involved. Supply shocks and risk shocks were relatively more important as well, although for the latter it was more sporadic within and across countries.

5.2.3 *Effect on curvature*

Finally, we examine the effect of oil price shocks on the curvature. Figure [8] presents the time-varying coefficients for oil-exporting, Figure [9] for oil-importing countries. Table [7] presents summary statistics.

Insert Table 7 here

In case of the oil-exporting countries, supply shocks had a significant effect around 2008, which was positive in Canada, in Mexico (followed by a decline into the negative territory) and Norway. In the UK, we can document a negative effect around 2009. In terms of the demand shocks, their effect was significant and negative in 2014, except for Norway and Venezuela. Another commonality is the significant negative effect around 2020, except for Canada and Venezuela. Additionally, we can document a significant, positive effect for the UK around 2012.

Risk shocks played a less significant role, with only Canada having more sustained periods of impact. In that case, we can document a positive effect around 2008 and a negative one around 2014.

Insert Figure 8 here

For the oil-importing countries, we can see a large, negative effect on the curvature provoked by supply shocks around 2013-2014, which for China was quite sustained. When it comes to the demand shocks, we can observe a negative effect on the curvature for all countries around 2014 except for South Korea. Additionally, in China we can observe a negative effect around 2010 and 2012. The 2010 episode is also true Germany, with an additional positive effect episode in 2015. In Japan, similarly to Germany, the negative effect documented in 2014 is followed by a more sustained period of positive effect in 2015. For South Korea, 2009 seems to be a more significant period, with a short positive effect. Finally, in the U.S. we can document a sustained, negative effect of demand shocks around 2005-2006. Risk shocks again play a less significant role, with Japan barely having any significant episodes, and South Korea and the U.S. having more of them.

Insert Figure 9 here

Summarizing the findings for the curvature, both supply and demand shocks had significant time periods for both country groups. For exporters, the effect of supply shocks on the curvature was positive around 2008, while it was negative for importers around 2013-2014. When it comes to demand shocks, in 2014 we could document a negative effect and in 2020 a positive effect for exporters, while for importers the key dates seem to be 2014, with a negative effect as well. Risk shocks again played a less significant role for both groups.

5.2.4 *Summary of the dynamic analysis*

Although the static analysis suggested that the effect of oil price shocks in the yield curve factors is not significant, the time-varying analysis revealed that the coefficients indeed vary over time, and periods of significant effects can be documented. Additionally, there seem to be periods, when countries within and across the country groups seems to behave similarly. We can also observe that significant periods are concentrated around some key dates, including 2008, 2014 and 2020, all of which can be related to some uncertainty episodes. In 2008-2009 the Global Financial Crisis caused turmoil in financial markets, significantly increasing economic policy uncertainty. 2014 was the aftermath of the eurozone crisis, with significant decline in the oil price. 2020 was the year of the coronavirus pandemic, which also induced a spike in economic policy uncertainty. Thus, the question whether uncertainty can have an effect on the connectedness between oil price shocks and yield curve factors naturally emerges.

6 The effect of uncertainty and risk on oil-yield curve connectedness

I concluded Section [5] by noting that the episodes when the time-varying coefficients relating oil price shocks to the yield curve is significant are concentrated around some key dates that can be associated with uncertainty episodes. In this section, I provide an analysis of whether U.S. economic policy uncertainty, geopolitical risk and the VIX index have a significant effect on the time-varying coefficients presented in Section [5]. The analysis consists of performing the regression described by Equation [3.8, the results of which can be found in Table [8] for oil-exporting countries and in Table [9] for oil-importing countries.

6.1 Oil-exporting countries

First, we look at the effect of uncertainty on the time varying coefficients connecting yield curve factors to oil price shocks. Generally, we can document that mostly the effect of the independent variables is significant at least at the 10% level, and sometimes they even explain a significant portion of the variation in the time-varying coefficients, as showcased by the R-squared values.

Insert Table 8 here

Looking at the effect on the oil price shock - level relationship, EPU is significant mostly for the risk shock effect, while GPR is significant for most of the shocks. Among the three independent variables, the VIX index is significant nearly for all cases. The R-squared values are lowest for the supply shock - level relationship (except for Venezuela), and for demand shocks they also hover around the low single digits. When it comes to the risk shock effect, the R-squared reaches 20.13% for Venezuela, although this is probably driven by the VIX index.

For the effects on slope, the role of EPU as a driver depends on the country. For example, in Mexico its effect is significant for all three shocks, while in Norway or Venezuela it is insignificant in all cases. On the other hand, GPR seems to play a more significant role, since for each country it is significant for at least one shock effect. Here again, VIX index seems to be the most significant drive. We can observe a high R-squared value in the UK for the supply shock - slope relationship, reaching 21.64%, driven by the EPU and the VIX index.

Finally, we turn to the coefficients between shocks and the curvature. In this case, the effect of EPU is very significant with only a few exceptions, and the coefficient of the GPR is also

significant in many cases. The VIX index also produces some significant values again. It is also in the case of the curvature that the highest R-squared values can be documented. In the Canada, uncertainty explains 17.56% of the variation of the risk shock - curvature connectedness, driven by the EPU and the VIX index. Interestingly, in Norway 15.6% of the variation of the supply shock - curvature is explained, while for the risk shock - curvature this value is 15.27%, with both having significant coefficients at the 1% level.

All in all, uncertainty indices are significant drivers of the oil price shock - yield curve factor connectedness, with the GPR and the VIX index playing the most significant role. Moreover, the strongest relationship has been observed in case of the oil price shock - curvature connections.

6.2 Oil-importing countries

Next, we look at oil-importing countries. Generally, we can again document significant coefficients, and in some cases relatively high R-squared values.

Insert Table 9 here

Starting with the effect on the relationship between the level and oil price shocks, we can see that EPU is significant in at least one case, except for Japan. In case of the GPR, we can document significant coefficients as well, while for the VIX nearly all coefficients are significant at the 1% level. It is also interesting that we find five double digit R-squared values, although four of these are related to the risk shock - level relatedness, which is likely to be driven by the VIX. In the case of South Korea, we can document that the uncertainty indicators can explain 16.62% of the variation of the supply shock - level coefficient.

Moving on to the slope, both EPU and GPR are just as significant as in the case of level. Moreover, in Japan 24.90% of the variation of the risk shock - slope relationship is explained by the model, likely to be driven by the VIX index to a large extent. For Germany, we can also see a 10.96% R-squared value for the supply shock - slope relationship, with all three independent variables' coefficients being significant. Overall, in the case of other relationships, the R-squared values are in the low-single digits.

Lastly, when it comes to the effect on the oil shock - curvature connectedness, we find significant coefficients again. Exceptions include China, South Korea and the U.S., where the GPR does not have a significant impact for any oil price shocks. The VIX and the EPU are significant for each country at least in one case. A higher R-squared can be documented in the case of the U.S. for the risk shock - curvature relationship, reaching 13.04%.

6.3 Is uncertainty an important driver?

According to the results of my model on the impact of uncertainty indices on oil price shock - yield curve connectedness we can conclude that in the majority of the cases uncertainty indices had a non-zero impact on the relationship, and in some cases they explained 10-20%

of their variation, which is non-negligible due to the large number of factors affecting such a relationship. There does not seem to be many differences between the oil-exporting and oil-importing country groups. Overall, R-squared values were higher in more cases when it comes to oil-importers, and the EPU index had more significant values relative to the GPR, than in the case of oil-exporters. This phenomenon may be due to the fact that oil-exporters' revenue sources related to the sale of crude oil can be easily disrupted by geopolitical conflicts, while in the case of oil-importers, EPU has a negative effect on consumption, and thus the purchase of oil, which can affect inflation, and thus rates. However, there is no clear reason indicated by this paper's model, thus this question should be the focus of future research.

7 Concluding remarks

This paper studied the time-varying connectedness between oil price shocks and components of the sovereign yield curve of 5 oil-exporting and 5 oil-importing countries. To do this, three main methodological approaches have been implemented. Firstly, I used the novel decomposition method of [Ready \(2018\)](#) to decompose oil price changes into supply, demand and risk shocks. Second, I implemented [Diebold and Li \(2006\)](#)'s modified Nelson-Siegel yield curve model to decompose the yield curves into three factors, which are level, slope and curvature. Finally, I used both static and dynamic regressions to see how oil price shocks are connected to these yield curve factors and how that has changed over time.

The second part of the analysis focused on how uncertainty impact the time-varying coefficients that resulted from the dynamic regressions. To do that, I have used the U.S. economic policy uncertainty index by [Baker et al. \(2016\)](#), the geopolitical risk index by [Caldara and Iacoviello \(2022\)](#) and the VIX index in a linear regression.

The static analysis shows significant coefficients could be identified for demand shocks both in the case of oil-exporting and oil-importing countries. In Canada and Norway, demand shocks have a positive effect on the level factor, while a negative effect on the slope. In terms of the oil-importing countries, in China we can find a significant negative effect of demand shocks on the slope, while in South Korea a significant positive effect on level. Overall, the static analysis seems to indicate that oil price shocks do not have a significant influence on yield curves.

However, the dynamic analysis reveals that the relationship is time-varying, with occasional significant episodes. Demand shocks had the most significant periods when it comes to affecting the level factor both in the case of oil-exporting and oil-importing countries. Demand shocks generally had some positive effect around 2014-2015 for oil exporters, just like in the case of importers. In addition, we can also observe a positive effect of demand shocks on importers' level factor around 2020. For both country group's level factor, supply and risk shocks do not play a very important role. In terms of the slope, oil-exporting countries seem more synchronized. Both supply and demand shocks play a significant role, although the sign of the effect was more homogenous. Risk shocks were again mostly insignificant. In case of the oil-importers, we can observe less synchronization, although demand shocks played the most significant role through the study period. Finally, the effect on curvature by supply and demand shocks was significant both by supply and demand shocks. For exporters, the effect on the curvature was positive around 2008 and negative around 2014. Demand shocks had a negative effect around 2014 for both groups, while they had a positive effect around 2020 for oil-exporters. Again, risk shocks

played a less important role. It is interesting to note that the episodes when the coefficients of the time-varying analysis are significant are periods related to a more uncertain episode, such as the 2008 crisis, the aftermath of the eurozone crisis or the COVID-19 pandemic. Thus, the question whether uncertainty is a driver emerges naturally.

In the second part of the analysis, we find that all three indices involved have significant effects on the time-varying coefficients, and in some cases, they explain a significant portion of the variation. The differences are minimal between country groups, although GPR seems to be a relatively more important factor for oil-exporters than for oil-importers.

The findings of this paper are similar to [Umar et al. \(2022\)](#) in that oil demand shocks have a strong impact on yield curve factors. In contrast, they attribute larger importance to risk shocks, whereas this paper found very little significance. The main reason behind this difference could be the methodology, as [Umar et al. \(2022\)](#) applies spillover indices, whereas this paper uses linear regressions. When it comes to the findings of [Ioannidis and Ka \(2018\)](#), this paper depicts a more nuanced picture, probably stemming from the time-varying analysis. Whilst [Ioannidis and Ka \(2018\)](#) claims that oil-specific demand shocks have a negative effect on the level for oil-importers while no such effect is observable for exporters, I show that the effects are sometimes synchronized across countries.

The findings of this paper have important implications for monetary policymaking and risk management. The fact that uncertainty is a significant driver of the oil-yield curve connectedness can guide central bankers to pay more attention during uncertainty episodes on the price of oil, and the macroeconomic channels that can link oil price shocks to the yield curve. For risk managers, it is key to evaluate the evolution of the price of oil even if a portfolio is predominantly composed of sovereign bonds, which seems to be the case especially during uncertainty episodes.

In terms of the limitations of the study, we can differentiate between methodological and conceptual limits. On the methods, the estimation of the yield curve factors may be improved if the decay term is allowed to be estimated by a non-linear regression. The oil price shock decomposition may be modified as in [Clements et al. \(2019\)](#) to account for precautionary demand shocks, although these shocks have little effect on the price of oil. Instead of linear regressions, a forecast error variance decomposition and an impulse response function or the spillover index developed by [Diebold and Yilmaz \(2012\)](#) could give a more nuanced picture. However, using these in a time-varying framework is very computing heavy, as the analysis is carried out on a daily basis. On the conceptual end, although this paper answers which shock impacts which yield curve factor, and to what extent uncertainty plays a role, it does not answer the question of how these connections are developed, and through which channels. The focus of further research should be identifying these channels and to put the findings presented here in a framework that can serve as a guide to policymakers and market actors to navigate the complex network of oil and fixed income markets.

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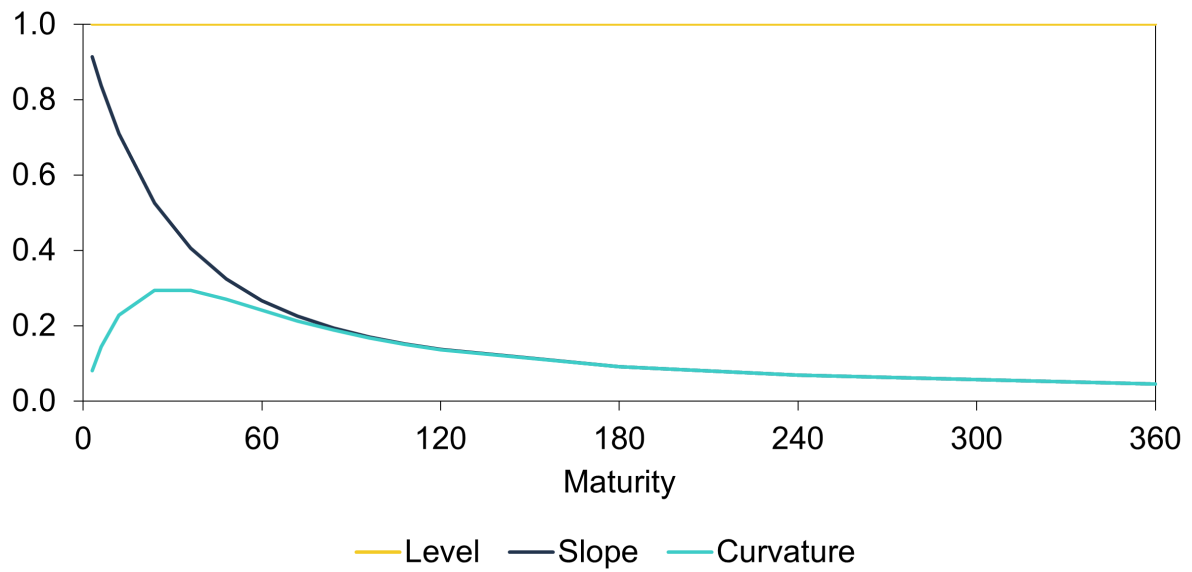
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A Figures and tables

Figure 1: Factor loadings of the modified Nelson-Siegel model



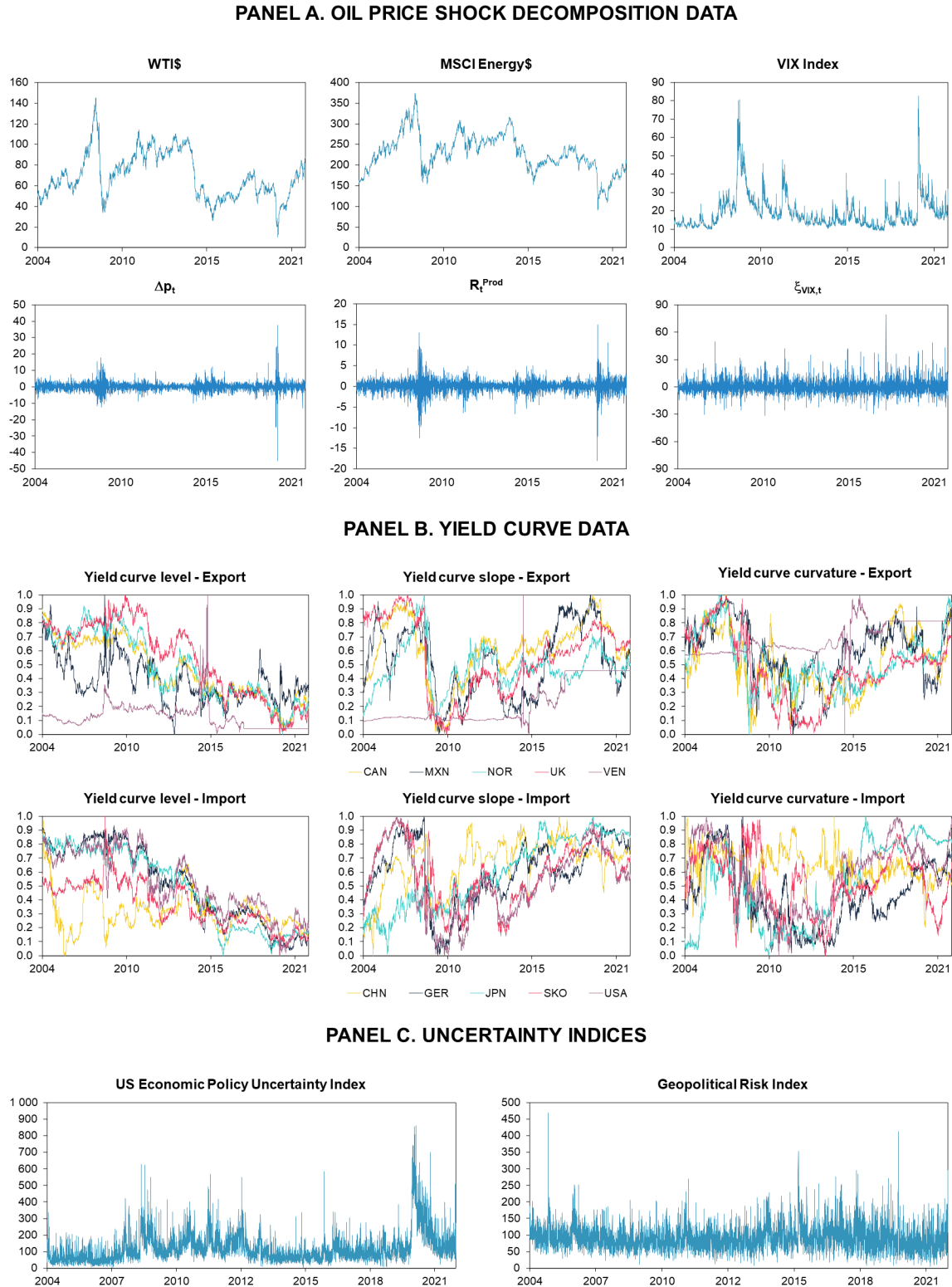
Note: This figure presents the yield curve factor loadings at different maturities ([Diebold & Li, 2006](#)). We get these values when the decay term is fixed at 0.0609. The maturities on the x-axis are expressed in months.

Table 1: Summary statistics of the yield curves

Country		3M	6M	1Y	2Y	3Y	4Y	5Y	6Y	7Y	8Y	9Y	10Y	15Y	20Y	30Y
CAN	Mean	1.47	1.53	1.62	1.77	1.94	2.10	2.22	2.34	2.46	2.57	2.67	2.77	3.10	3.25	3.12
	Std. dev.	1.21	1.24	1.22	1.20	1.21	1.22	1.23	1.23	1.25	1.25	1.24	1.25	1.24	1.26	1.15
	Min.	0.09	0.09	0.12	0.15	0.23	0.26	0.28	0.32	0.34	0.37	0.41	0.45	0.67	0.72	0.71
	Max.	4.70	4.81	4.83	4.79	4.82	4.81	4.80	4.85	5.07	5.15	5.24	5.30	5.69	5.97	5.62
MXN	Mean	5.86	5.90	5.98	6.20	6.45	6.67	6.85	7.03	7.20	7.33	7.44	7.53	7.96	8.29	8.47
	Std. dev.	1.86	1.85	1.79	1.66	1.54	1.47	1.39	1.38	1.39	1.38	1.35	1.34	1.21	1.17	1.17
	Min.	2.69	2.80	2.98	3.42	3.91	4.00	4.10	4.18	4.25	4.41	4.52	4.61	5.08	5.66	5.82
	Max.	10.08	10.36	10.38	10.45	10.55	10.68	10.90	10.93	11.09	11.50	11.76	11.78	12.12	12.42	12.46
NOR	Mean	1.76	1.80	1.85	1.93	2.08	2.23	2.36	2.48	2.59	2.67	2.75	2.82	2.89	2.90	2.89
	Std. dev.	1.35	1.39	1.37	1.35	1.32	1.34	1.33	1.32	1.33	1.32	1.31	1.31	1.27	1.25	1.25
	Min.	-0.12	-0.12	-0.13	-0.15	-0.06	-0.03	0.01	0.09	0.14	0.21	0.27	0.33	0.48	0.49	0.49
	Max.	5.91	6.12	6.09	5.73	5.53	5.34	5.27	5.26	5.26	5.28	5.27	5.27	5.27	5.27	5.27
UK	Mean	1.54	1.57	1.60	1.75	1.92	2.09	2.22	2.35	2.47	2.58	2.69	2.78	3.10	3.24	3.20
	Std. dev.	2.00	2.01	1.96	1.90	1.86	1.80	1.75	1.70	1.67	1.64	1.61	1.59	1.48	1.38	1.30
	Min.	-0.21	-0.21	-0.17	-0.16	-0.18	-0.14	-0.11	-0.08	-0.05	-0.01	0.05	0.11	0.37	0.54	0.53
	Max.	5.92	5.94	5.92	5.94	5.93	5.92	5.85	5.79	5.76	5.71	5.64	5.58	5.32	5.26	5.01
VEN	Mean	29.01	27.57	26.54	25.35	23.97	22.27	20.56	19.14	18.14	17.41	16.84	16.50	14.89	11.85	11.30
	Std. dev.	29.50	26.43	24.24	21.48	18.49	15.21	12.30	10.12	8.52	7.43	6.75	6.32	4.95	3.13	3.32
	Min.	2.29	2.35	2.71	4.75	5.29	5.82	5.99	6.16	6.31	6.35	6.53	6.63	6.94	6.66	6.18
	Max.	136.45	183.20	131.37	61.72	54.72	49.66	43.82	38.92	35.55	33.40	33.30	33.57	52.83	61.53	61.53
CHN	Mean	2.39	2.45	2.56	2.76	2.97	3.14	3.27	3.36	3.46	3.53	3.60	3.66	3.81	3.88	3.96
	Std. dev.	0.76	0.76	0.71	0.66	0.63	0.60	0.59	0.58	0.58	0.58	0.58	0.60	0.66	0.63	0.61
	Min.	0.56	0.62	0.79	1.07	1.26	1.55	1.77	1.96	2.14	2.30	2.54	2.62	2.66	2.65	2.65
	Max.	4.17	4.26	4.28	4.40	4.47	4.65	4.90	4.95	5.19	5.25	5.36	5.53	6.32	6.22	6.13
GER	Mean	0.66	0.71	0.77	0.86	0.99	1.15	1.29	1.44	1.58	1.70	1.81	1.91	2.34	2.53	2.53
	Std. dev.	1.55	1.58	1.62	1.63	1.67	1.71	1.71	1.72	1.74	1.73	1.72	1.71	1.78	1.78	1.64
	Min.	-1.05	-1.03	-0.99	-0.99	-1.02	-1.03	-1.01	-0.98	-0.97	-0.94	-0.91	-0.87	-0.71	-0.59	-0.47
	Max.	4.35	4.46	4.67	4.68	4.68	4.77	4.71	4.70	4.68	4.68	4.68	4.68	5.02	5.29	5.30
JPN	Mean	0.03	0.05	0.07	0.13	0.19	0.27	0.35	0.44	0.52	0.63	0.72	0.80	1.18	1.45	1.70
	Std. dev.	0.21	0.22	0.26	0.32	0.37	0.43	0.48	0.52	0.57	0.62	0.65	0.68	0.76	0.79	0.82
	Min.	-0.38	-0.34	-0.35	-0.36	-0.37	-0.38	-0.39	-0.38	-0.37	-0.35	-0.32	-0.28	-0.13	0.01	0.04
	Max.	0.67	0.67	0.84	1.10	1.30	1.48	1.59	1.70	1.84	1.95	2.03	2.06	2.47	2.66	3.15
SKO	Mean	2.28	2.37	2.49	2.76	3.05	3.32	3.54	3.69	3.84	3.99	4.15	4.27	4.65	4.80	4.71
	Std. dev.	1.63	1.66	1.64	1.58	1.57	1.57	1.57	1.52	1.48	1.46	1.45	1.44	1.39	1.33	1.39
	Min.	0.30	0.32	0.35	0.40	0.50	0.63	0.79	1.00	1.15	1.31	1.37	1.44	1.69	1.89	1.71
	Max.	7.40	7.26	7.43	8.02	8.23	8.58	9.21	9.37	9.56	9.59	9.67	9.70	9.70	9.57	9.52
USA	Mean	1.23	1.32	1.42	1.61	1.82	2.04	2.25	2.43	2.61	2.76	2.88	2.98	3.42	3.64	3.69
	Std. dev.	1.53	1.59	1.56	1.46	1.39	1.32	1.27	1.24	1.22	1.21	1.20	1.19	1.28	1.28	1.07
	Min.	0.00	0.01	0.04	0.11	0.11	0.15	0.20	0.29	0.35	0.41	0.46	0.50	0.66	0.94	1.08
	Max.	5.19	5.43	5.50	5.33	5.32	5.30	5.29	5.30	5.32	5.38	5.40	5.41	5.67	6.38	5.55

Note: This table presents summary statistics of the yield curve data obtained for the sample period. The countries have been divided into two groups, Canada (CAN), Mexico (MXN), Norway (NOR), United Kingdom (UK) and Venezuela (VEN) belonging to the oil-exporters, while China (CHN), Germany (GER), Japan (JPN), South-Korea (SKO) and United States (USA) pertaining to the oil-importers.

Figure 2: Time series of the data used for the analysis during the study period



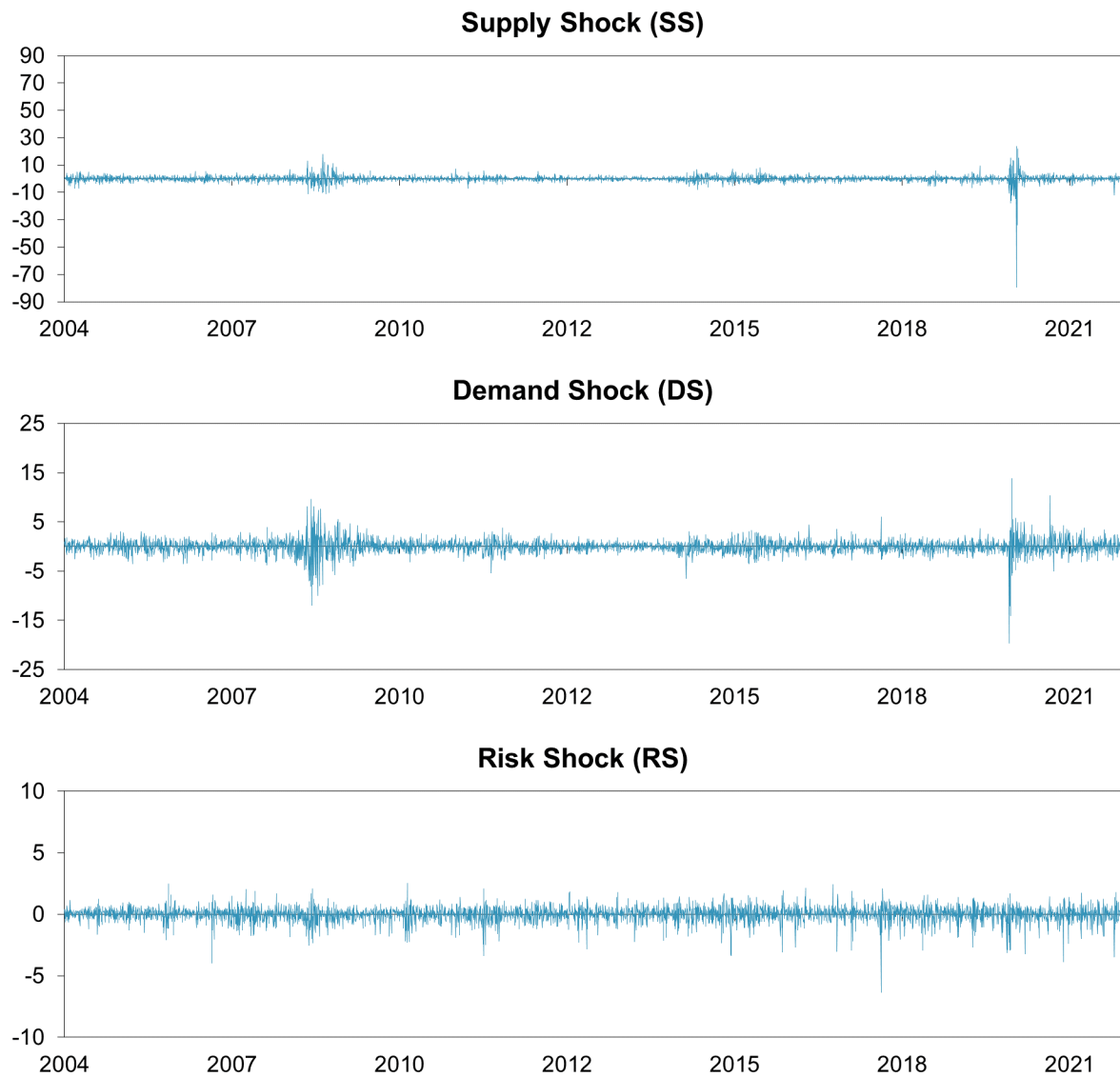
Note: This figure presents the time series of the data used for the analysis during the study period (10/01/2004 - 01/28/2022). Panel A. presents the data used for the oil price shock decomposition. Panel B. presents the yield curve factors of oil-exporting and oil-importing countries on a 0 to 1 scale. Panel C. presents the U.S. Economic Policy Uncertainty Index and the Geopolitical Risk Index.

Table 2: Summary statistics of the data used for the oil price decomposition, the oil price shocks and the uncertainty indices

Variable	N	Mean	Std. dev.	Median	Min.	Max.	Skewness	Kurtosis	J-B
ξ_{VIX}	4365	-0.028	2.941	0.100	-82.517	27.358	-5.60	156.18	4290462.7***
R^{Prod}	4365	-0.006	1.588	0.046	-22.079	13.021	-1.42	19.99	54003.7***
Δp	4365	-0.025	7.490	-0.736	-31.347	79.093	1.24	6.91	3890.3***
Supply Shock	4365	-0.010	2.462	0.048	-79.677	23.790	-8.01	266.61	12685141.5***
Demand Shock	4365	-0.010	1.400	-0.006	-19.698	13.786	-0.87	20.65	57216.3***
Risk Shock	4365	0.002	0.603	0.059	-6.366	2.523	-1.24	6.91	3890.3***
USEPU	6329	117.25	88.65	93.34	3.32	861.10	2.46	9.41	17242.4***
GPR	6329	92.10	38.50	86.96	3.57	469.20	1.28	4.67	2470.6***

Note: This table presents summary statistics of the data used for the oil price shock identification, the oil price shocks themselves and the uncertainty indices. The column

Figure 3: Time series of the resulting structural oil price shocks



Note: This figure presents the time series of the decomposed structural oil price shocks of [Ready \(2018\)](#). It can be seen from the relative magnitude of the shocks on the charts that supply shocks represent the largest portion of the variation in the price of oil.

Table 3: Estimated coefficients of the static model for oil-exporting countries

Yield curve parameter	β_0	β_{SS}	β_{DS}	β_{RS}	R-squared (%)
CANADA					
Level (s.e.)	3.2354*** (0.0178)	-0.0014 (0.0072)	0.0216* (0.0127)	-0.0013 (0.0295)	0.07
Slope (s.e.)	-1.661*** (0.0188)	0.0015 (0.0076)	-0.0248* (0.0134)	0.0185 (0.0312)	0.09
Curvature (s.e.)	-2.5772*** (0.0241)	0.0063 (0.0098)	0.0014 (0.0172)	0.0213 (0.04)	0.02
MEXICO					
Level (s.e.)	8.4404*** (0.0169)	-0.0081 (0.0069)	0.0152 (0.0121)	-0.0152 (0.028)	0.07
Slope (s.e.)	-2.3426*** (0.0276)	0.0097 (0.0112)	-0.0222 (0.0197)	0.0141 (0.0458)	0.05
Curvature (s.e.)	-4.1814*** (0.0417)	-0.0039 (0.0169)	-0.0371 (0.0298)	-0.0145 (0.0691)	0.04
NORWAY					
Level (s.e.)	3.0123*** (0.0186)	-0.0001 (0.0075)	0.0227* (0.0133)	-0.0201 (0.0308)	0.08
Slope (s.e.)	-1.2093*** (0.0148)	-0.0034 (0.006)	-0.0271** (0.0106)	-0.0539** (0.0246)	0.27
Curvature (s.e.)	-1.6217*** (0.0186)	0.008 (0.0076)	0.0087 (0.0133)	-0.00001 (0.0309)	0.04
UNITED KINGDOM					
Level (s.e.)	3.344*** (0.0218)	0.0002 (0.0089)	0.0181 (0.0156)	-0.0175 (0.0362)	0.04
Slope (s.e.)	-1.7777*** (0.0261)	0.0038 (0.0106)	-0.0113 (0.0186)	0.0319 (0.0433)	0.02
Curvature (s.e.)	-3.1306*** (0.0433)	-0.0065 (0.0176)	0.0054 (0.0309)	-0.0159 (0.0718)	0.00
VENEZUELA					
Level (s.e.)	10.3945*** (0.0702)	-0.0309 (0.0285)	-0.0151 (0.0502)	-0.0895 (0.1165)	0.04
Slope (s.e.)	18.6151*** (0.4871)	0.0293 (0.198)	0.0073 (0.3481)	-0.2545 (0.8082)	0.00
Curvature (s.e.)	23.3418*** (0.4139)	0.0275 (0.1682)	-0.0751 (0.2957)	-0.0427 (0.6867)	0.00

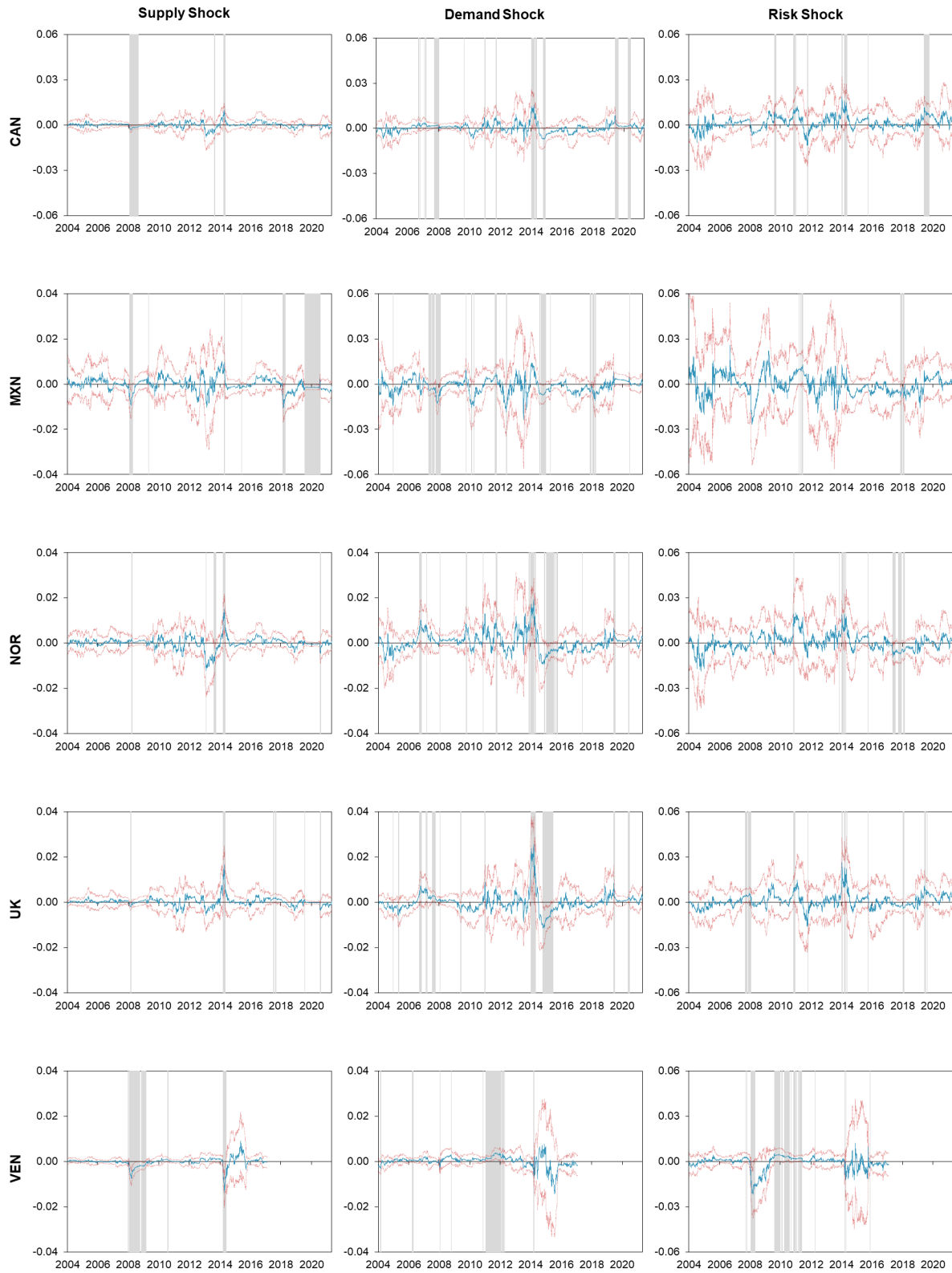
Note: This table presents the results of the static regressions for oil-exporting countries, according to Equation [3.6]. Numbers between parantheses are the standard errors. The superscripts *, **, and *** indicate the significance of the coefficients at 10%, 5% and 1% level, respectively.

Table 4: Estimated coefficients of the static model for oil-importing countries

Yield curve parameter	β_0	β_{SS}	β_{DS}	β_{RS}	R-squared (%)
CHINA					
Level (s.e.)	4.0139*** (0.0081)	0.0029 (0.0033)	0.0017 (0.0058)	0.004 (0.0134)	0.02
Slope (s.e.)	-1.6308*** (0.0128)	-0.0007 (0.0052)	-0.021** (0.0091)	0.005 (0.0212)	0.12
Curvature (s.e.)	-1.4042*** (0.0103)	-0.0013 (0.0042)	-0.0042 (0.0074)	-0.0067 (0.0171)	0.01
GERMANY					
Level (s.e.)	2.5566*** (0.0259)	0.0003 (0.0105)	0.0253 (0.0185)	-0.0258 (0.043)	0.05
Slope (s.e.)	-1.7019*** (0.017)	0.0015 (0.0069)	-0.0192 (0.0121)	-0.0016 (0.0282)	0.06
Curvature (s.e.)	-3.5637*** (0.026)	-0.0006 (0.0106)	0.0136 (0.0186)	-0.0183 (0.0431)	0.02
JAPAN					
Level (s.e.)	1.5359*** (0.0135)	-0.0003 (0.0055)	0.0109 (0.0096)	-0.0168 (0.0223)	0.04
Slope (s.e.)	-1.1834*** (0.0101)	-0.0006 (0.0041)	-0.0095 (0.0072)	0.0053 (0.0168)	0.04
Curvature (s.e.)	-3.3913*** (0.0215)	0.0029 (0.0087)	-0.0117 (0.0154)	0.0038 (0.0357)	0.02
SOUTH KOREA					
Level (s.e.)	4.9595*** (0.0208)	-0.0039 (0.0084)	0.0254* (0.0148)	-0.0157 (0.0344)	0.08
Slope (s.e.)	-2.5175*** (0.0203)	0.0019 (0.0083)	-0.008 (0.0145)	-0.0004 (0.0337)	0.01
Curvature (s.e.)	-3.2471*** (0.03)	-0.0081 (0.0122)	-0.0104 (0.0215)	0.0024 (0.0498)	0.02
UNITED STATES					
Level (s.e.)	3.8006*** (0.0185)	0.0024 (0.0075)	0.018 (0.0132)	0.0071 (0.0306)	0.05
Slope (s.e.)	-2.3189*** (0.0239)	0.0021 (0.0097)	-0.014 (0.0171)	0.0318 (0.0396)	0.03
Curvature (s.e.)	-3.8781*** (0.0392)	-0.0034 (0.0159)	-0.0254 (0.028)	0.0954 (0.065)	0.07

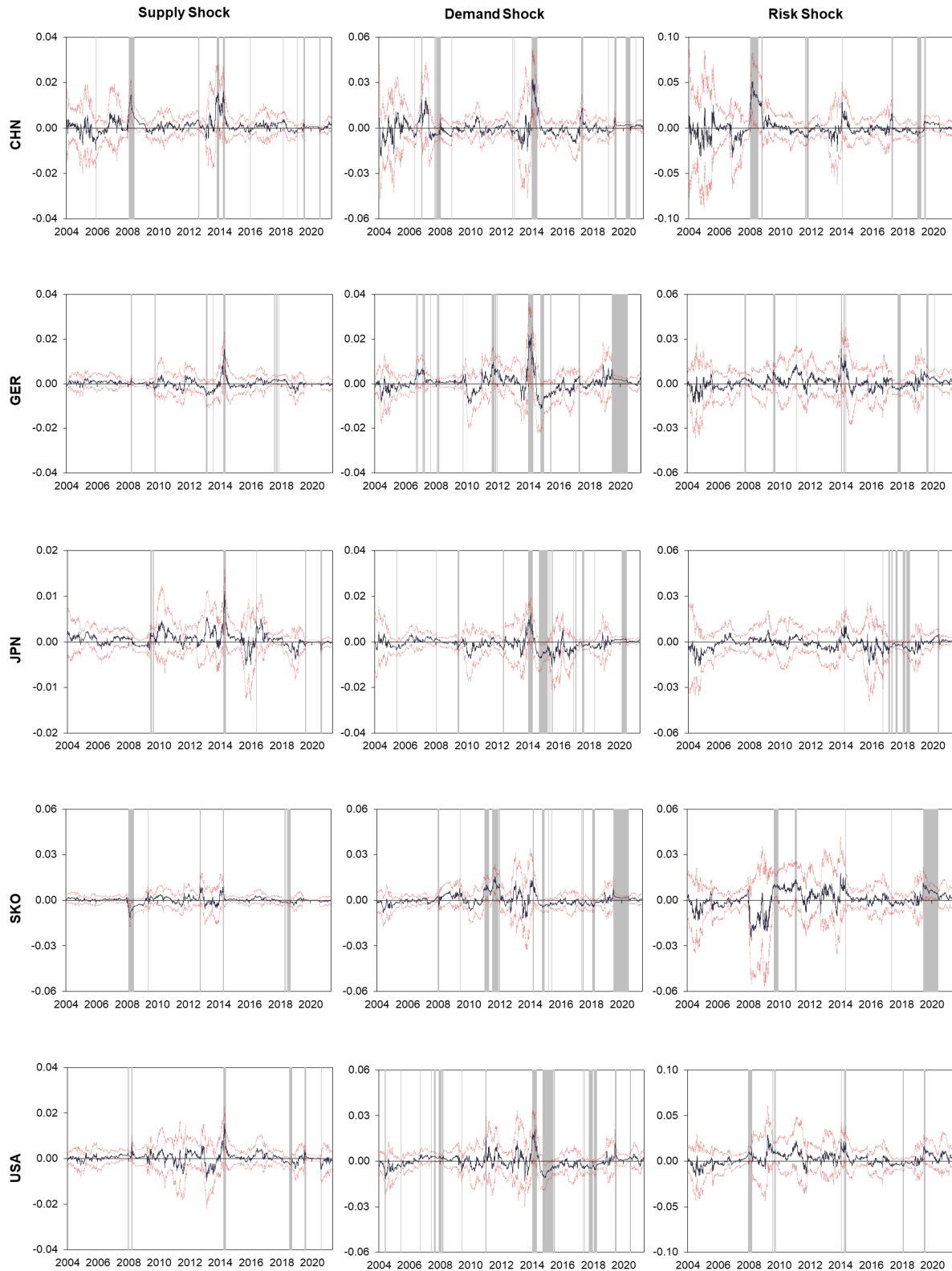
Note: This table presents the results of the static regressions for oil-importing countries, according to Equation [3.6]. Numbers between parantheses are the standard errors. The superscripts *, **, and *** indicate the significance of the coefficients at 10%, 5% and 1% level, respectively.

Figure 4: Dynamic effect of oil shocks on oil-exporting countries' level factor



Note: Estimates of the time-varying coefficients of the effect of structural oil price shocks on the oil-exporting countries' yield curve level factor. The red curves represent the lower and upper boundary of the 95% confidence intervals. The vertical light grey shades mark the periods when the parameter is significant at the 5% level.

Figure 5: Dynamic effect of oil shocks on oil-importing countries' level factor



Note: Estimates of the time-varying coefficients of the effect of structural oil price shocks on the oil-importing countries' yield curve level factor. The red curves represent the lower and upper boundary of the 95% confidence intervals. The vertical light grey shades mark the periods when the parameter is significant at the 5% level.

Table 5: Descriptive statistics of the time-varying coefficients of oil shocks on the level factor

	Oil-xporting countries					Oil-importing countries				
	CAN	MXN	NOR	UK	VEN	CHN	GER	JPN	SKO	USA
	Beta	SS								
	LVL									
<i>Supply Shock effect</i>										
mean	0.0000	-0.0001	0.0001	0.0003	-0.0001	0.0010	0.0001	0.0006	0.0000	0.0004
median	0.0000	-0.0002	0.0003	0.0003	0.0001	0.0005	0.0001	0.0005	0.0001	0.0004
min.	-0.0083	-0.0107	-0.0122	-0.0058	-0.0139	-0.0098	-0.0056	-0.0051	-0.0117	-0.0100
max.	0.0097	0.0101	0.0150	0.0166	0.0091	0.0163	0.0156	0.0111	0.0091	0.0155
std. dev.	0.0017	0.0028	0.0025	0.0019	0.0019	0.0030	0.0019	0.0016	0.0021	0.0023
skewness	-0.0070	-0.1217	-0.4993	2.3883	-1.7407	1.7539	1.8075	1.1107	-0.4736	0.4991
kurtosis	4.3628	1.4508	7.5524	17.9290	11.5840	5.9179	13.0003	5.9771	5.0689	6.3679
# observations	4365	4365	4365	4365	3299	4365	4365	4365	4365	4365
J-B	337.8***	447.3***	3950.7***	44684.9***	11794.5***	3786.3***	20565.2***	2509.5***	941.6***	2244.2***
<i>Demand Shock effect</i>										
mean	0.00032	-0.0015	0.00052	0.00004	0.00015	-0.00009	0.00026	-0.00086	0.00032	-0.00034
median	0.00048	-0.00094	0.00049	-0.00017	0.00059	-0.00062	0.0004	-0.00048	-0.00042	-0.00026
min.	-0.00902	-0.02356	-0.00943	-0.01135	-0.01442	-0.01873	-0.01138	-0.01083	-0.01206	-0.01329
max.	0.01557	0.01425	0.01987	0.026	0.00782	0.03255	0.02231	0.01285	0.01538	0.02094
std. dev.	0.00298	0.00465	0.00397	0.00387	0.00246	0.00573	0.00397	0.00261	0.00377	0.00416
skewness	0.73992	-0.34061	0.68884	1.8598	-1.93041	1.62387	0.98407	0.19748	0.92924	0.79123
kurtosis	2.9877	1.11667	1.48412	9.70925	7.35851	6.29735	5.12538	2.52451	1.68398	2.7667
# observations	4365	4365	4365	4365	3299	4365	4365	4365	4365	4365
J-B	398.3***	729.5***	763.1***	10703.2***	4660.2***	3895.8***	1526.1***	69.5***	943.2***	351.7***
<i>Risk Shock effect</i>										
mean	0.0014	-0.0006	0.0004	0.0010	-0.0008	-0.00008	0.00066	-0.00142	0.00056	0.00233
median	0.0013	-0.0007	0.0001	0.0004	0.0005	-0.00124	0.00057	-0.00098	0.00081	0.00181
min.	-0.0137	-0.0268	-0.0185	-0.0161	-0.0219	-0.03235	-0.01346	-0.016	-0.0265	-0.01728
max.	0.0186	0.0259	0.0202	0.0265	0.0123	0.05117	0.0237	0.01098	0.0179	0.02896
std. dev.	0.0041	0.0067	0.0053	0.0044	0.0046	0.00985	0.00411	0.00365	0.00621	0.00615
skewness	0.03845	-0.2021	0.46988	0.82288	-1.95215	1.74153	0.59182	-0.58334	-1.01422	0.48557
kurtosis	0.5858	0.7302	1.4411	3.0521	4.3125	6.35567	2.27705	1.18792	2.04803	0.85146
# observations	4365	4365	4365	4365	3299	4365	4365	4365	4365	4365
J-B	1061.1***	966.7***	602.6***	493.1***	2332.1***	4254.5***	349.9***	844.8***	913.2***	1011.1***

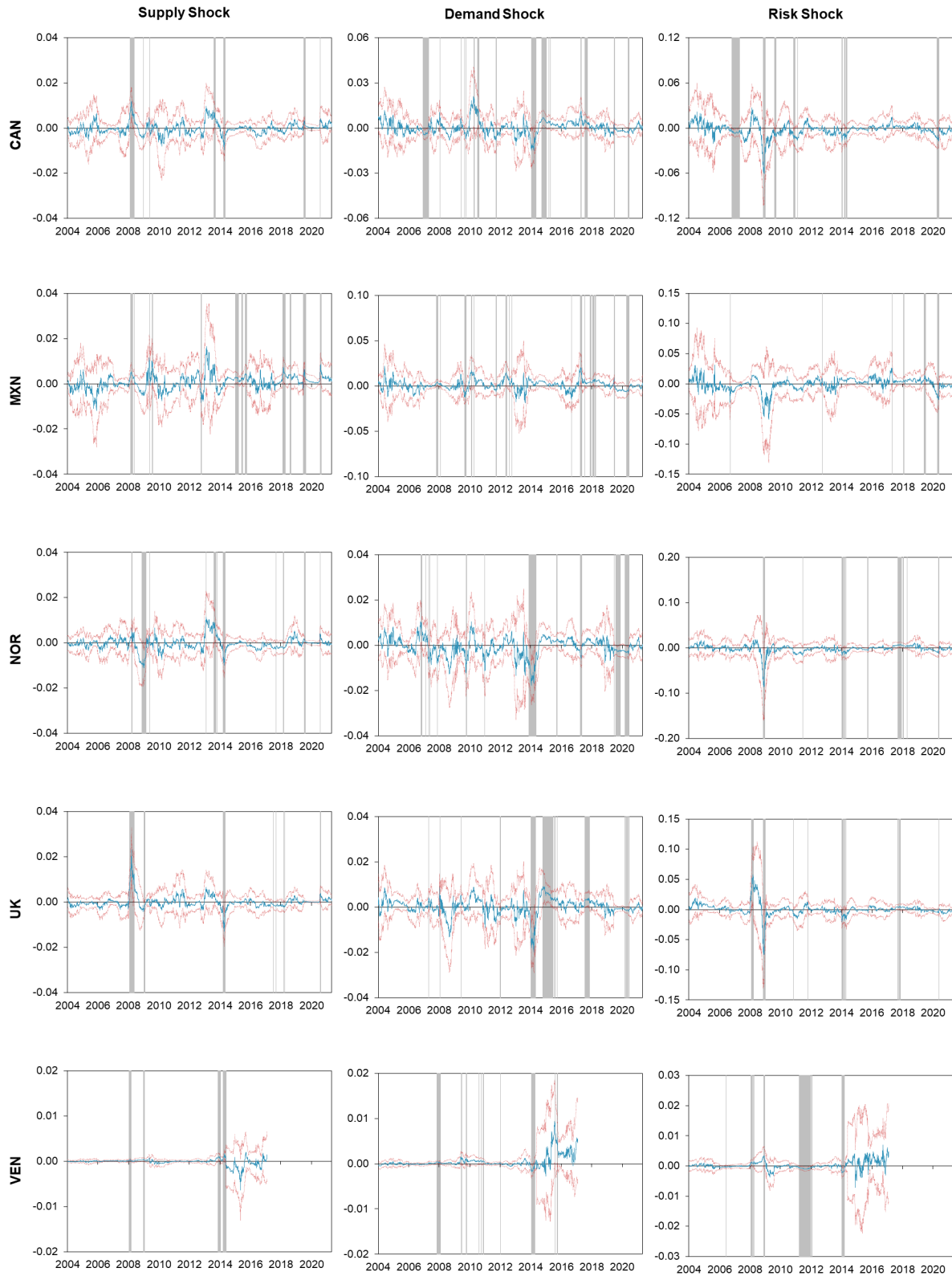
Note: The table provides summary statistics of the time-varying coefficients of oil price shocks on the level factor. *, ** and *** indicate that the null hypothesis of the Jarque-Bera test is rejected at 10%, 5% and 1% level, respectively.

Table 6: Descriptive statistics of the time-varying coefficients of oil shocks on the slope factor

	Oil-xporting countries					Oil-importing countries				
	CAN	MXN	NOR	UK	VEN	CHN	GER	JPN	SKO	USA
<i>Supply Shock effect</i>										
mean	-0.0002	0.0006	-0.0003	0.0000	-0.0001	-0.0005	0.0001	-0.0010	-0.0005	-0.0004
median	-0.0004	0.0006	-0.0004	-0.0002	0.0000	-0.0001	0.0002	-0.0009	-0.0004	-0.0006
min.	-0.0096	-0.0119	-0.0110	-0.0129	-0.0063	-0.0100	-0.0163	-0.0089	-0.0137	-0.0104
max.	0.0119	0.0164	0.0116	0.0232	0.0020	0.0092	0.0169	0.0039	0.0108	0.0091
std. dev.	0.0026	0.0033	0.0028	0.0026	0.0007	0.0023	0.0029	0.0016	0.0028	0.0024
skewness	0.7703	0.2633	0.1845	2.3915	-2.5457	-0.6323	0.2880	-0.4670	-0.5022	0.3048
kurtosis	2.1973	1.8944	3.4963	16.6854	11.4754	1.9336	5.7993	1.1999	2.0867	1.2660
# observations	4365	4365	4365	4365	3299	4365	4365	4365	4365	4365
J-B	548.8***	272.8***	69.6***	38223.9***	13437.2***	497.7***	1485.5***	748***	335.2***	464.4***
<i>Demand Shock effect</i>										
mean	0.00043	0.00092	-0.00069	0.00023	0.00049	-0.00032	-0.0006	0.00102	0.00067	0.00055
median	0.00011	0.0009	-0.00042	0.00028	0.00005	0.00038	-0.00059	0.00073	0.00033	0.00014
min.	-0.01528	-0.01876	-0.01767	-0.01991	-0.0028	-0.04506	-0.02326	-0.0089	-0.02203	-0.01415
max.	0.02089	0.0219	0.01047	0.00918	0.00941	0.01456	0.01616	0.00911	0.02321	0.02154
std. dev.	0.0044	0.00525	0.00399	0.00358	0.0014	0.00731	0.0048	0.00311	0.0053	0.00434
skewness	0.60195	0.26828	-0.74651	-1.19682	2.79117	-2.0696	-0.30688	-0.10273	-0.28037	0.28105
kurtosis	2.47814	1.04967	1.46341	4.441	9.64367	7.54971	2.10385	-0.05268	1.97613	1.14834
# observations	4365	4365	4365	4365	3299	4365	4365	4365	4365	4365
J-B	313.1***	744.2***	834.8***	1419.7***	10350.7***	6880.8***	214.6***	1702.5***	247.8***	514.7***
<i>Risk Shock effect</i>										
mean	-0.0024	-0.0003	-0.0016	0.0004	0.0002	-0.0012	-0.00152	0.00152	-0.00186	-0.0023
median	-0.0018	0.0014	-0.0010	-0.0002	0.0000	0.0005	-0.00172	0.00121	-0.00144	-0.00245
min.	-0.0603	-0.0595	-0.0857	-0.0744	-0.0072	-0.06611	-0.08205	-0.01449	-0.05044	-0.03057
max.	0.0270	0.0309	0.0183	0.0574	0.0071	0.01803	0.03936	0.02207	0.03705	0.03403
std. dev.	0.0085	0.0102	0.0091	0.0101	0.0013	0.0099	0.01015	0.00462	0.00902	0.00792
skewness	-1.57899	-1.5778	-4.30317	-0.25341	0.60265	-2.23606	-1.50402	0.29124	-0.22897	0.08195
kurtosis	8.9411	5.7404	31.0743	16.2390	2.8244	9.26644	15.73658	1.29668	3.62645	2.2348
# observations	4365	4365	4365	4365	3299	4365	4365	4365	4365	4365
J-B	8233.4***	3176.9***	156819.3***	31924.1***	203.9***	10779.4***	31149.5***	589.4***	109.5***	84.2***

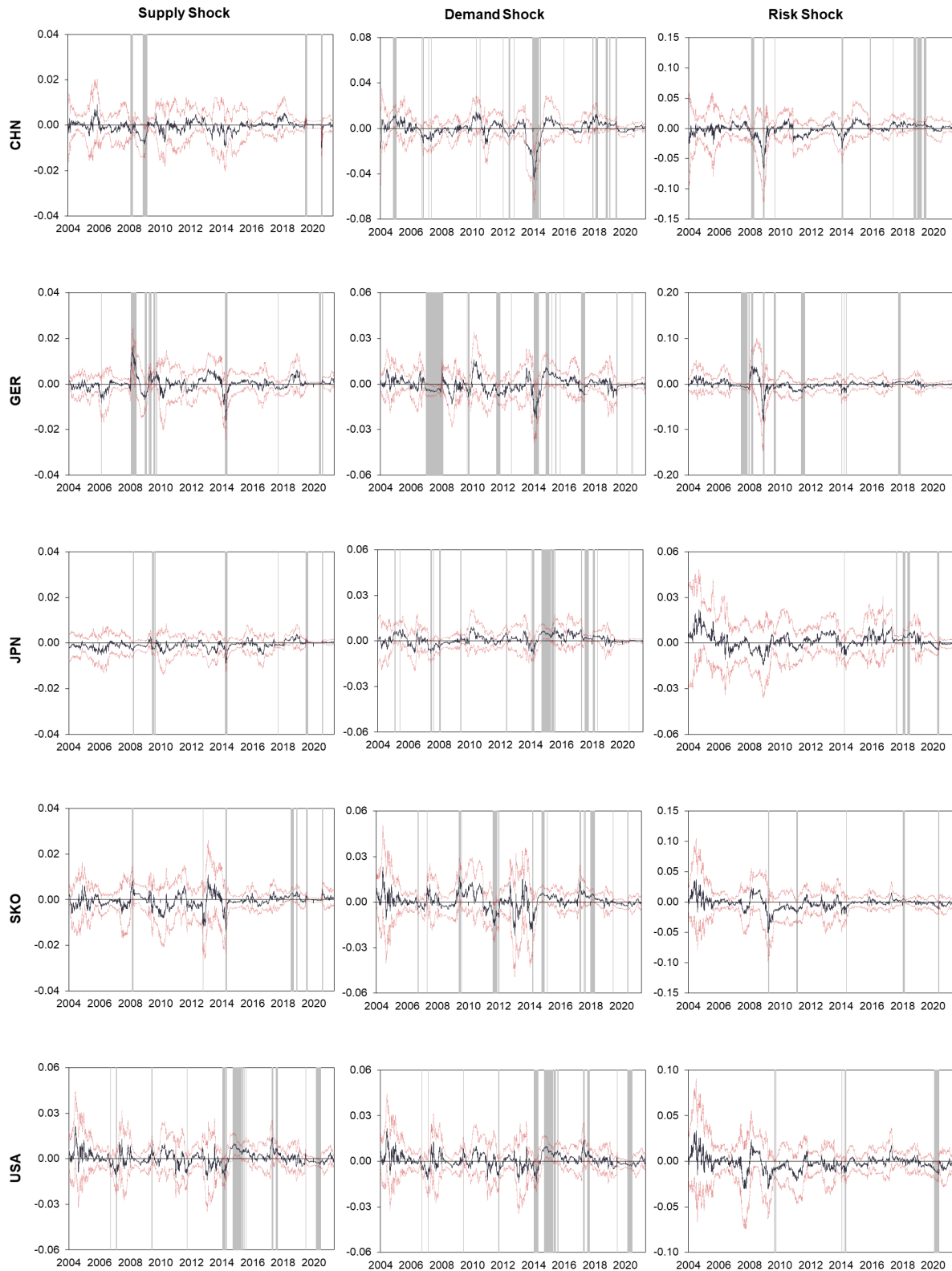
Note: The table provides summary statistics of the time-varying coefficients of oil price shocks on the slope factor. *, ** and *** indicate that the null hypothesis of the Jarque-Bera test is rejected at 10%, 5% and 1% level, respectively.

Figure 6: Dynamic effect of oil shocks on oil-exporting countries' slope factor



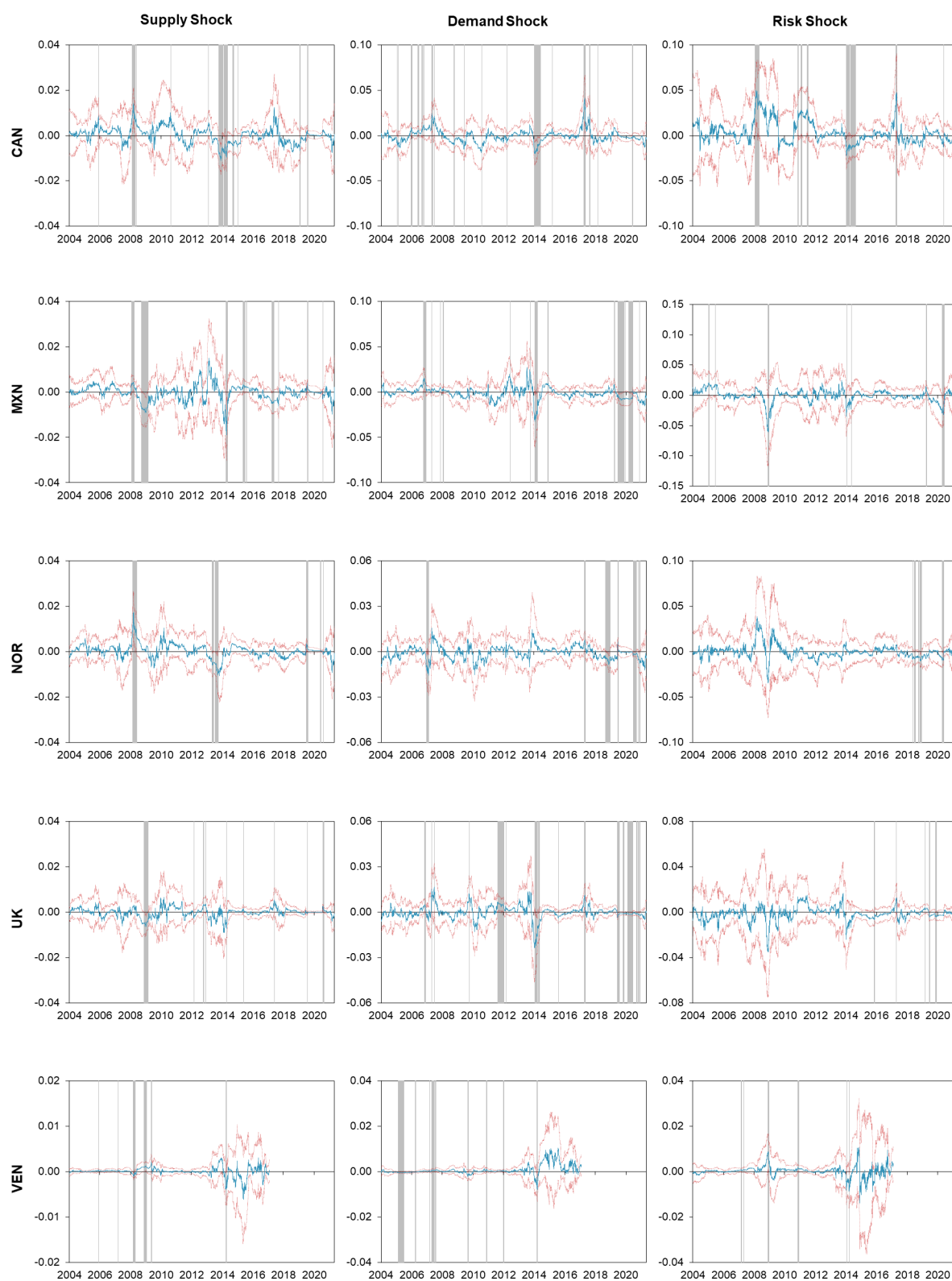
Note: Estimates of the time-varying coefficients of the effect of structural oil price shocks on the oil-exporting countries' yield curve slope factor. The red curves represent the lower and upper boundary of the 95% confidence intervals. The vertical light grey shades mark the periods when the parameter is significant at the 5% level.

Figure 7: Dynamic effect of oil shocks on oil-importing countries' slope factor



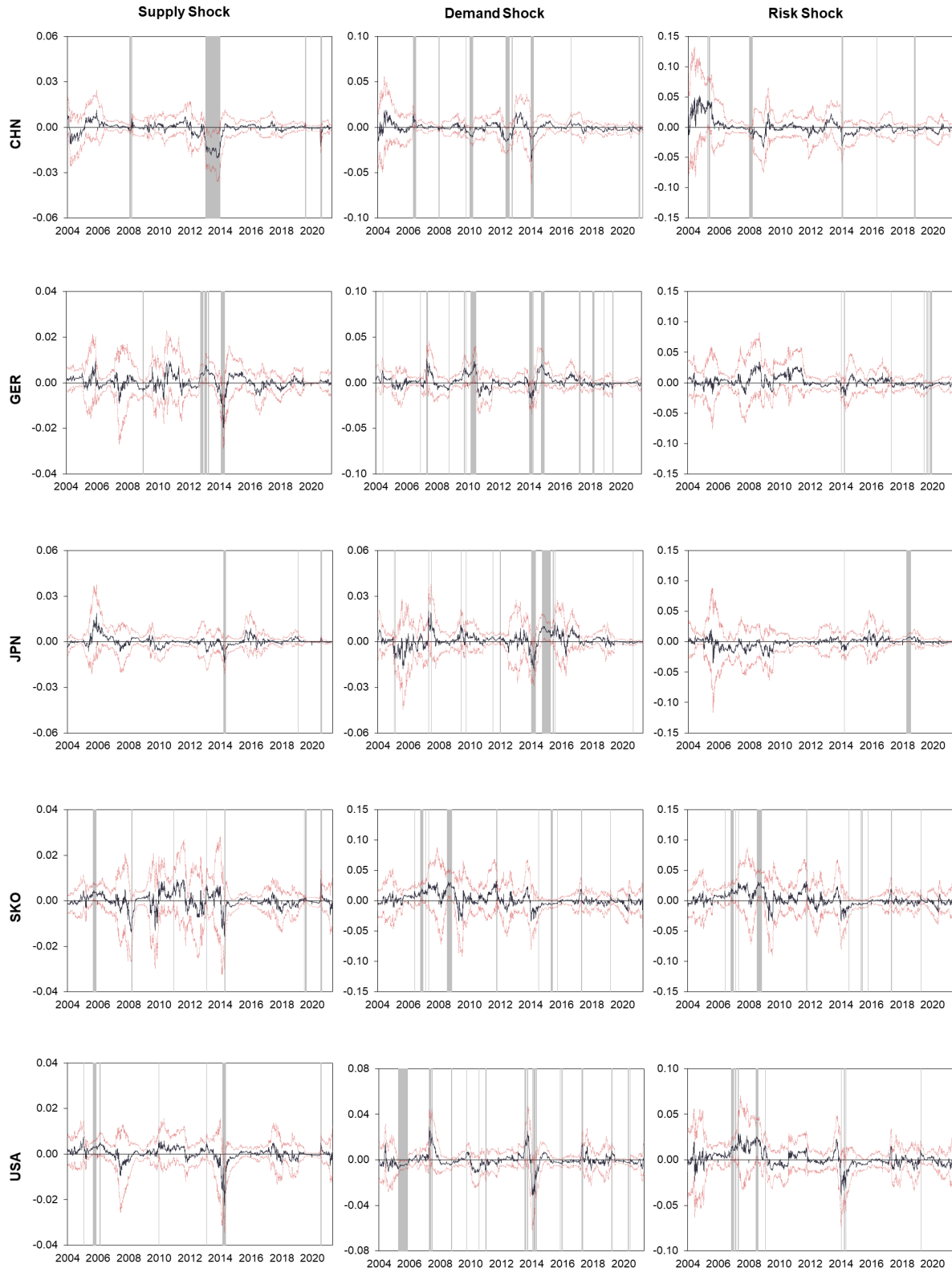
Note: Estimates of the time-varying coefficients of the effect of structural oil price shocks on the oil-importing countries' yield curve slope factor. The red curves represent the lower and upper boundary of the 95% confidence intervals. The vertical light grey shades mark the periods when the parameter is significant at the 5% level.

Figure 8: Dynamic effect of oil shocks on oil-exporting countries' curvature factor



Note: Estimates of the time-varying coefficients of the effect of structural oil price shocks on the oil-exporting countries' yield curve curvature factor. The red curves represent the lower and upper boundary of the 95% confidence intervals. The vertical light grey shades mark the periods when the parameter is significant at the 5% level.

Figure 9: Dynamic effect of oil shocks on oil-importing countries' curvature factor



Note: Estimates of the time-varying coefficients of the effect of structural oil price shocks on the oil-importing countries' yield curve curvature factor. The red curves represent the lower and upper boundary of the 95% confidence intervals. The vertical light grey shades mark the periods when the parameter is significant at the 5% level.

Table 7: Descriptive statistics of the time-varying coefficients of oil shocks on the curvature factor

	Oil-xporting countries					Oil-importing countries				
	CAN	MXN	NOR	UK	VEN	CHN	GER	JPN	SKO	USA
<i>Supply Shock effect</i>										
mean	0.0002	-0.0004	0.0003	-0.0001	0.0000	-0.0010	0.0002	0.0002	-0.0001	0.0001
median	0.0006	-0.0001	0.0004	0.0000	0.0001	-0.0001	0.0001	-0.0001	-0.0001	0.0004
min.	-0.0110	-0.0190	-0.0108	-0.0091	-0.0061	-0.0205	-0.0198	-0.0143	-0.0158	-0.0227
max.	0.0142	0.0148	0.0173	0.0066	0.0031	0.0112	0.0097	0.0188	0.0095	0.0074
std. dev.	0.0034	0.0034	0.0029	0.0020	0.0010	0.0046	0.0030	0.0030	0.0033	0.0029
skewness	0.0124	-0.4944	0.2998	-0.6673	-1.6698	-1.9841	-1.0846	0.8922	-0.6665	-2.5792
kurtosis	0.7084	3.5089	4.2036	1.8026	7.3032	4.8360	6.3329	5.3501	2.6951	13.2820
# observations	4365	4365	4365	4365	3299	4365	4365	4365	4365	4365
J-B	955.2***	224.9***	328.8***	584.8***	4078.5***	3477***	2876.2***	1583.6***	340.1***	18189.7***
<i>Demand Shock effect</i>										
mean	-0.00059	-0.00119	-0.00073	-0.00008	0.00082	-0.00068	0.00103	0.00085	0.00003	-0.00072
median	-0.00114	-0.00127	-0.00043	-0.00031	0.00025	-0.00077	0.00002	0.00061	-0.00047	-0.00122
min.	-0.02027	-0.03285	-0.01573	-0.02361	-0.00796	-0.03756	-0.02322	-0.01893	-0.02994	-0.03179
max.	0.04115	0.02721	0.01561	0.0166	0.01044	0.01879	0.02608	0.0204	0.03003	0.02901
std. dev.	0.0067	0.00623	0.00414	0.0042	0.00215	0.00562	0.00622	0.00439	0.00715	0.00595
skewness	1.11572	-0.34996	-0.00382	-0.96762	1.74297	-0.93387	0.61519	-0.51146	0.66436	-0.04067
kurtosis	5.20316	3.64865	0.84622	6.04328	4.86158	6.15297	1.47304	2.64449	3.24437	6.57767
# observations	4365	4365	4365	4365	3299	4365	4365	4365	4365	4365
J-B	1788.4***	165.6***	843.7***	2365.6***	2146.7***	2442.5***	699.4***	213.3***	332***	2329.2***
<i>Risk Shock effect</i>										
mean	0.0032	-0.0007	-0.0002	-0.0015	0.0002	0.00028	0.00189	-0.00146	0.00197	0.00112
median	0.0010	0.0000	-0.0006	-0.0012	0.0004	-0.00171	-0.00037	-0.00053	0.00017	-0.00018
min.	-0.0225	-0.0608	-0.0347	-0.0352	-0.0139	-0.03444	-0.02283	-0.03508	-0.03393	-0.03876
max.	0.0496	0.0243	0.0386	0.0167	0.0108	0.05197	0.03434	0.0202	0.03265	0.02945
std. dev.	0.0117	0.0098	0.0072	0.0058	0.0023	0.01195	0.00844	0.00666	0.01014	0.00853
skewness	1.21137	-1.72302	1.20653	-1.10569	-0.13906	1.67542	0.91347	-0.84616	0.38057	0.16389
kurtosis	1.5486	6.8402	6.5286	5.5790	5.8796	4.04769	1.08469	1.63353	0.72937	1.61316
# observations	4365	4365	4365	4365	3299	4365	4365	4365	4365	4365
J-B	1450.7***	4841.9***	3323.6***	2099.1***	1150.5***	2241.8***	1274.2***	860.5***	1043.1***	369.3***

Note: The table provides summary statistics of the time-varying coefficients of oil price shocks on the curvature factor. *, ** and *** indicate that the null hypothesis of the Jarque-Bera test is rejected at 10%, 5% and 1% level, respectively.

Table 8: Effect of uncertainty and risk indices on the relationship between different oil price shocks and yield curve parameters in oil-exporting countries

Shock - Parameter	β_0	β_{EPU}	β_{GPR}	β_{VIX}	R-squared (%)
CANADA					
SS - Level	0.0412***	0.0142***	0.0106	-0.377***	3.22
(s.e.)	(0.01)	(0.0036)	(0.0069)	(0.0331)	
DS - Level	-0.0428**	0.0116*	-0.0586***	0.6376***	5.76
(s.e.)	(0.0172)	(0.0062)	(0.0118)	(0.0568)	
RS - Level	0.1005***	0.0843***	-0.0605***	0.0433	3.75
(s.e.)	(0.0241)	(0.0087)	(0.0166)	(0.0797)	
SS - Slope	-0.1897***	-0.0101*	0.0301***	0.8088***	7.33
(s.e.)	(0.0145)	(0.0053)	(0.01)	(0.0481)	
DS - Slope	0.0256	0.0229**	0.0975***	-0.5645***	1.95
(s.e.)	(0.0258)	(0.0094)	(0.0178)	(0.0855)	
RS - Slope	-0.4203***	0.0025	0.2522***	-0.3941**	1.59
(s.e.)	(0.05)	(0.0181)	(0.0345)	(0.1657)	
SS - Curvature	-0.1765***	0.0039	-0.0023	1.0079***	7.56
(s.e.)	(0.0195)	(0.0071)	(0.0135)	(0.0647)	
DS - Curvature	-0.0719*	-0.0461***	0.0502*	0.0717	0.41
(s.e.)	(0.0396)	(0.0143)	(0.0273)	(0.1311)	
RS - Curvature	-0.6532***	-0.134***	-0.0021	5.9074***	17.56
(s.e.)	(0.063)	(0.0228)	(0.0434)	(0.2086)	
MEXICO					
SS - Level	0.0953***	-0.0011	0.042***	-0.7821***	7.55
(s.e.)	(0.0159)	(0.0058)	(0.0109)	(0.0526)	
DS - Level	-0.1899***	0.0102	-0.0677***	0.5123***	1.78
(s.e.)	(0.0273)	(0.0099)	(0.0188)	(0.0905)	
RS - Level	0.1223***	0.0767***	-0.1176***	-0.7581***	1.34
(s.e.)	(0.0397)	(0.0144)	(0.0273)	(0.1314)	
SS - Slope	0.0905***	0.016**	-0.0704***	0.1315**	1.36
(s.e.)	(0.0192)	(0.007)	(0.0132)	(0.0635)	
DS - Slope	0.2225***	-0.0395***	-0.0064	-0.4185***	1.4
(s.e.)	(0.0309)	(0.0112)	(0.0213)	(0.1022)	
RS - Slope	-0.1439**	0.0823***	0.21***	-1.0228***	1.33
(s.e.)	(0.0597)	(0.0216)	(0.0411)	(0.1977)	
SS - Curvature	0.0033	0.02***	-0.013	-0.2548***	0.36
(s.e.)	(0.0203)	(0.0073)	(0.014)	(0.0671)	
DS - Curvature	-0.0386	-0.11***	0.0573**	-0.08	2.7
(s.e.)	(0.0364)	(0.0132)	(0.0251)	(0.1205)	
RS - Curvature	0.1069*	-0.0969***	0.1692***	-1.2592***	3.96
(s.e.)	(0.0571)	(0.0207)	(0.0394)	(0.1892)	

cont'd

Shock - Parameter	β_0	β_{EPU}	β_{GPR}	β_{VIX}	R-squared (%)
NORWAY					
SS - Level	-0.0506***	0.0015	0.0359***	0.124**	0.44
(s.e.)	(0.0146)	(0.0053)	(0.0101)	(0.0485)	
DS - Level	-0.0982***	0.0087	-0.0392**	0.9474***	5.7
(s.e.)	(0.0228)	(0.0083)	(0.0157)	(0.0756)	
RS - Level	-0.2353***	0.0071	-0.0464**	1.671***	9.26
(s.e.)	(0.0297)	(0.0108)	(0.0205)	(0.0985)	
SS - Slope	-0.0413**	0.0047	0.0003	0.0064	0.02
(s.e.)	(0.0164)	(0.0059)	(0.0113)	(0.0542)	
DS - Slope	0.0678***	-0.0093	0.0546***	-0.9567***	6.03
(s.e.)	(0.0229)	(0.0083)	(0.0158)	(0.0758)	
RS - Slope	-0.1536***	0.0349*	0.1912***	-1.2769***	2.22
(s.e.)	(0.0534)	(0.0193)	(0.0368)	(0.1767)	
SS - Curvature	-0.1702***	-0.0164***	-0.0319***	1.3108***	15.6
(s.e.)	(0.016)	(0.0058)	(0.011)	(0.0529)	
DS - Curvature	-0.0861***	0.0005	0.0546***	-0.2247***	0.58
(s.e.)	(0.0244)	(0.0089)	(0.0168)	(0.0809)	
RS - Curvature	-0.6831***	-0.1233***	0.1212***	3.5364***	15.27
(s.e.)	(0.0391)	(0.0142)	(0.0269)	(0.1295)	
UNITED KINGDOM					
SS - Level	0.0654***	-0.0038	0.0063	-0.2009***	1.27
(s.e.)	(0.0109)	(0.004)	(0.0075)	(0.0361)	
DS - Level	-0.0547**	0.0025	-0.0446***	0.53***	2.04
(s.e.)	(0.0227)	(0.0082)	(0.0156)	(0.0752)	
RS - Level	-0.0698***	0.0384***	-0.0436**	0.8694***	5.73
(s.e.)	(0.0252)	(0.0091)	(0.0174)	(0.0835)	
SS - Slope	-0.2464***	-0.0256***	0.004	1.4332***	21.64
(s.e.)	(0.0136)	(0.0049)	(0.0094)	(0.0452)	
DS - Slope	0.0853***	-0.0093	0.0491***	-0.5347***	2.79
(s.e.)	(0.0209)	(0.0076)	(0.0144)	(0.0693)	
RS - Slope	-0.6332***	-0.1114***	0.1755***	3.26***	6.69
(s.e.)	(0.0576)	(0.0209)	(0.0397)	(0.1908)	
SS - Curvature	-0.0723***	0.0244***	0.0438***	-0.0665*	1.31
(s.e.)	(0.0116)	(0.0042)	(0.008)	(0.0385)	
DS - Curvature	0.0058	0.029***	-0.025	-0.1081	0.32
(s.e.)	(0.0248)	(0.009)	(0.0171)	(0.0823)	
RS - Curvature	-0.2603***	0.0853***	0.0254	-0.0642	1.37
(s.e.)	(0.0339)	(0.0123)	(0.0234)	(0.1123)	

cont'd

Shock - Parameter	β_0	β_{EPU}	β_{GPR}	β_{VIX}	R-squared (%)
VENEZUELA					
SS - Level	0.1004***	0.02***	0.0001	-0.6959***	11.37
(s.e.)	(0.0094)	(0.0034)	(0.0065)	(0.031)	
DS - Level	-0.0028	0.0161***	-0.0459***	0.1966***	2.6
(s.e.)	(0.0129)	(0.0047)	(0.0089)	(0.0427)	
RS - Level	0.2862***	0.1188***	-0.0362**	-2.3279***	20.13
(s.e.)	(0.0212)	(0.0077)	(0.0146)	(0.0704)	
SS - Slope	-0.0082	0.0003	0.003	0.0289	0.09
(s.e.)	(0.0055)	(0.002)	(0.0038)	(0.0183)	
DS - Slope	0.0938***	0.0002	0.0174**	-0.2777***	1.62
(s.e.)	(0.0126)	(0.0046)	(0.0087)	(0.0417)	
RS - Slope	0.0495***	0.0028	-0.0058	-0.1757***	0.49
(s.e.)	(0.0125)	(0.0045)	(0.0086)	(0.0415)	
SS - Curvature	0.0023	0.0043**	0.0056	-0.0362**	0.19
(s.e.)	(0.0053)	(0.0019)	(0.0037)	(0.0176)	
DS - Curvature	0.1051***	-0.0232***	0.0246***	-0.1585***	2.66
(s.e.)	(0.0118)	(0.0043)	(0.0081)	(0.0391)	
RS - Curvature	0.0447***	0.0054	-0.0263***	-0.0034	0.3
(s.e.)	(0.0124)	(0.0045)	(0.0085)	(0.041)	

Note: This table presents the results of the uncertainty regressions for oil-exporting countries, according to Equation [3.7]. Numbers between parantheses are the standard errors. The superscripts *, **, and *** indicate the significance of the coefficients at 10%, 5% and 1% level, respectively.

Table 9: Effect of uncertainty and risk indices on the relationship between different oil price shocks and yield curve parameters in oil-importing countries

Shock - Parameter	β_0	β_{EPU}	β_{GPR}	β_{VIX}	R-squared (%)
CHINA					
SS - Level	-0.1174***	-0.0476***	0.0439***	1.1669***	9.16
(s.e.)	(0.0171)	(0.0062)	(0.0118)	(0.0565)	
DS - Level	-0.0071	-0.018	-0.0448*	0.3332***	0.32
(s.e.)	(0.0339)	(0.0123)	(0.0233)	(0.1122)	
RS - Level	-1.089***	-0.0654***	-0.0372	6.2533***	30.95
(s.e.)	(0.0485)	(0.0176)	(0.0334)	(0.1606)	
SS - Slope	-0.0075	0.0633***	0.0341***	-0.752***	7.45
(s.e.)	(0.0131)	(0.0047)	(0.009)	(0.0432)	
DS - Slope	0.0789*	0.0488***	-0.0079	-0.8276***	0.77
(s.e.)	(0.0431)	(0.0156)	(0.0297)	(0.1429)	
RS - Slope	0.242***	0.1418***	0.0872**	-3.1975***	6.74
(s.e.)	(0.0566)	(0.0205)	(0.039)	(0.1874)	
SS - Curvature	-0.2277***	0.0097	-0.0034	0.6436***	1.96
(s.e.)	(0.0267)	(0.0097)	(0.0184)	(0.0886)	
DS - Curvature	-0.0047	-0.0755***	0.0328	-0.0637	1.54
(s.e.)	(0.033)	(0.012)	(0.0228)	(0.1094)	
RS - Curvature	-0.0047	-0.0755***	0.0328	-0.0637	8.60
(s.e.)	(0.033)	(0.012)	(0.0228)	(0.1094)	
GERMANY					
SS - Level	0.0029	-0.0004	0.019**	-0.0699*	0.32
(s.e.)	(0.0112)	(0.0041)	(0.0077)	(0.037)	
DS - Level	-0.0007	0.02**	-0.0779***	0.4398***	2.59
(s.e.)	(0.0232)	(0.0084)	(0.016)	(0.0769)	
RS - Level	-0.0807***	0.0846***	-0.0833***	0.7158***	9.92
(s.e.)	(0.0231)	(0.0084)	(0.0159)	(0.0765)	
SS - Slope	-0.2141***	-0.0189***	0.0228**	1.1544***	10.96
(s.e.)	(0.0164)	(0.0059)	(0.0113)	(0.0544)	
DS - Slope	-0.0258	-0.0067	0.1014***	-0.6809***	2.90
(s.e.)	(0.028)	(0.0102)	(0.0193)	(0.0928)	
RS - Slope	-0.6406***	-0.133***	0.2518***	1.9989***	3.00
(s.e.)	(0.0592)	(0.0215)	(0.0408)	(0.1961)	
SS - Curvature	-0.0337*	-0.0096	0.0123	0.2757***	0.53
(s.e.)	(0.0178)	(0.0064)	(0.0123)	(0.0589)	
DS - Curvature	0.1704***	-0.0056	0.0949***	-0.8256***	2.18
(s.e.)	(0.0364)	(0.0132)	(0.0251)	(0.1207)	
RS - Curvature	-0.395***	-0.1202***	0.0958***	3.2618***	9.30
(s.e.)	(0.0476)	(0.0173)	(0.0328)	(0.1576)	

cont'd

Shock - Parameter	β_0	β_{EPU}	β_{GPR}	β_{VIX}	R-squared (%)
JAPAN					
SS - Level	0.0925***	0.0024	0.004	-0.2215***	1.58
(s.e.)	(0.0092)	(0.0033)	(0.0063)	(0.0303)	
DS - Level	-0.1586***	-0.0015	-0.0246**	0.5224***	3.61
(s.e.)	(0.0152)	(0.0055)	(0.0105)	(0.0503)	
RS - Level	-0.4086***	0.0027	-0.0403***	1.5978***	17.13
(s.e.)	(0.0197)	(0.0071)	(0.0136)	(0.0651)	
SS - Slope	-0.1199***	0.019***	-0.0066	0.0555*	1.52
(s.e.)	(0.0094)	(0.0034)	(0.0065)	(0.0312)	
DS - Slope	0.2504***	0.02***	0.0308**	-1.058***	8.70
(s.e.)	(0.0176)	(0.0064)	(0.0121)	(0.0583)	
RS - Slope	0.6009***	0.0402***	0.0168	-2.6798***	24.90
(s.e.)	(0.0237)	(0.0086)	(0.0163)	(0.0785)	
SS - Curvature	-0.0196	-0.0285***	0.0617***	0.0332	1.38
(s.e.)	(0.0175)	(0.0063)	(0.0121)	(0.058)	
DS - Curvature	0.0677***	0.0177*	-0.0044	0.0121	0.13
(s.e.)	(0.026)	(0.0094)	(0.0179)	(0.0861)	
RS - Curvature	0.035	0.1155***	0.1365***	-2.356***	8.69
(s.e.)	(0.0377)	(0.0137)	(0.026)	(0.1249)	
SOUTH KOREA					
SS - Level	0.1715***	0.0482***	-0.0136*	-1.0871***	16.62
(s.e.)	(0.0112)	(0.0041)	(0.0078)	(0.0372)	
DS - Level	-0.0515**	0.0374***	-0.1035***	0.7687***	7.91
(s.e.)	(0.0214)	(0.0078)	(0.0148)	(0.0709)	
RS - Level	0.3203***	0.2502***	-0.111***	-2.2632***	11.00
(s.e.)	(0.0347)	(0.0126)	(0.0239)	(0.115)	
SS - Slope	-0.2037***	-0.027***	0.0374***	0.7752***	4.94
(s.e.)	(0.016)	(0.0058)	(0.011)	(0.0531)	
DS - Slope	0.0467	-0.0071	0.0841***	-0.2985***	0.83
(s.e.)	(0.0313)	(0.0113)	(0.0215)	(0.1035)	
RS - Slope	-0.4883***	-0.1529***	0.2261***	1.2804***	2.68
(s.e.)	(0.0527)	(0.0191)	(0.0363)	(0.1746)	
SS - Curvature	0.0996***	0.039***	0.0124	-0.8474***	4.17
(s.e.)	(0.019)	(0.0069)	(0.0131)	(0.063)	
DS - Curvature	0.0107	-0.0555***	0.0101	0.233*	0.31
(s.e.)	(0.0423)	(0.0153)	(0.0291)	(0.14)	
RS - Curvature	-0.1216**	-0.1647***	-0.0227	2.7596***	4.50
(s.e.)	(0.0587)	(0.0213)	(0.0405)	(0.1945)	

cont'd

Shock - Parameter	β_0	β_{EPU}	β_{GPR}	β_{VIX}	R-squared (%)
UNITED STATES					
SS - Level	-0.0083	0.0084*	0.0144	0.1139***	0.46
(s.e.)	(0.0133)	(0.0048)	(0.0092)	(0.0441)	
DS - Level	-0.2014***	0.0245***	-0.0758***	1.1378***	9.06
(s.e.)	(0.0235)	(0.0085)	(0.0162)	(0.0777)	
RS - Level	-0.2014***	0.0245***	-0.0758***	1.1378***	17.26
(s.e.)	(0.0235)	(0.0085)	(0.0162)	(0.0777)	
SS - Slope	-0.1881***	-0.0042	0.017*	0.6954***	6.39
(s.e.)	(0.0138)	(0.005)	(0.0095)	(0.0459)	
DS - Slope	0.1208***	-0.0234**	0.0531***	-0.4918***	2.24
(s.e.)	(0.0254)	(0.0092)	(0.0175)	(0.0842)	
RS - Slope	-0.3336***	-0.1135***	0.2037***	0.1252	2.59
(s.e.)	(0.0463)	(0.0168)	(0.0319)	(0.1533)	
SS - Curvature	0.0353**	0.026***	0.011	-0.3325***	0.89
(s.e.)	(0.0169)	(0.0061)	(0.0116)	(0.0559)	
DS - Curvature	-0.0195	0.0056	-0.0192	-0.2079*	0.09
(s.e.)	(0.0352)	(0.0128)	(0.0243)	(0.1166)	
RS - Curvature	-0.4861***	-0.1163***	0.0028	3.8051***	13.04
(s.e.)	(0.0471)	(0.0171)	(0.0324)	(0.156)	

Note: This table presents the results of the uncertainty regressions for oil-importing countries, according to Equation [3.7]. Numbers between parantheses are the standard errors. The superscripts *, **, and *** indicate the significance of the coefficients at 10%, 5% and 1% level, respectively.