Systemic risk: What do we know about oil price volatility shocks?

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Abstract

We use a sample of 11,448 US firms for a 30-year period to test the effect of different types of oil price volatility shocks on financial stability, by means of systemic risk measures. Results indicate that oil price volatility does not always positively affects systemic risk. More specifically, decomposing oil price volatility shocks, we find that supply-side and idiosyncratic oil price volatility shocks lessen the systemic risk, while the opposite is true when we consider the effects from demand-side oil price volatility shocks. Our key findings also hold for different types of firm risk (i.e., unsystematic, systematic and total risk). Furthermore, industry-specific analysis supports the baseline analysis and unveils heterogeneous responses depending on the extent of company association with the oil market. Portfolio analysis reveals that our results also hold across different portfolio settings. Our results are robust when we also control for major events and different time frames. Important policy implications are also discussed.

Keywords: financial stability, systemic risk, oil price volatility, supply-side shocks, aggregate demand shocks, idiosyncratic shocks

JEL Classification: G12, G3, Q4

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1 Introduction

For more than half a century, numerous studies try to identify the determinants of various types of firm risk due to their impact on risk premium estimation, portfolio construction, hedging strategies, cost of capital measurement and corporate financial decisions, among others (see, for instance Hamada, 1972; Robichek and Cohn, 1974; Andersen et al., 2005; Gaspar and Massa, 2006; Becchetti et al., 2015; Cheung, 2016; Abdoh and Varela, 2017). Some of the common determinants are capital structure, firm's fundamentals, corporate social responsibility, market competition, as well as, industrial production and GDP. Key among these risk factors is the contribution of each firm on systemic risk given its direct impact on financial stability. Particularly in the aftermath of the Global Financial Crisis of 2007-08, the attention on systemic risk by the financial regulators (a concept closely associated with the potential implosion of the financial system) has gained much prominence. Exogenous or endogenous shocks that could trigger simultaneous failures of firms put substantial pressure in any economy, which could lead to a financial crisis. Hence, identifying the drivers of systemic risk is of immense importance for regulators and market participants (Acharya et al., 2012). To date, the majority of studies focuses on the determinants of systemic risk in the banking sector (see, among others, López-Espinosa et al., 2012; Li and Zinna, 2014; Adrian and Brunnermeier, 2016; Varotto and Zhao, 2018; Borri and Di Giorgio, 2022).

Nevertheless, despite the fact that the firm risk literature is rich in identifying systemic risk's factors, there is another strand of literature in finance, with strong links to firm risk, which has flourished significantly over the last fifteen years, and examines the impact of oil prices and oil price volatility on firms' financial performance. Oil prices and oil price volatility could trigger important exogenous or endogenous shocks, which can cause economic turbulence. This line of research was mainly initiated with the seminal paper by Jones and Kaul (1996), yet due to the increased financialisation of the oil market, as well as, the need for sustainable energy usage by firms, the research efforts have recently intensified.[1]

The effect of oil price volatility on businesses and particularly strategic decision–making suggests that corporations may become very cautious and hesitant with regard to making potential investments, in the light of oil price fluctuations (see, Elder and Serletis, 2010; Bloom, 2014). Gupta and Krishnamurti (2018) identify oil price risk as a factor that has a strong impact on firm's cash flows and revenues. In turn, it could be argued that, heightened oil price volatility might result in firms having to pay a higher risk premium as a compensation for increased levels of operational risk. Indeed, oil is a major input of production and therefore volatile oil prices are expected to affect the cost of producing goods and services and consequently firms' profitability and valuation. Despite that determinants of firms' volatility have been widely studied in the literature (e.g., Ang et al., 2009), and the same holds for the effects of oil prices on stock behaviour (e.g., Jones and Kaul, 1996), the effects of oil price volatility on firms' systemic remains rather underdeveloped.

We place emphasis on oil price volatility due to its growing importance in recent years following the remarkable financialisation of commodity markets and the subsequent strengthening of the link between oil and financial markets (see indicatively, Degiannakis and Filis, 2017; Chatziantoniou et al., 2021). As recently pointed out by Gao et al. (2021), heightened levels of oil price uncertainty could result in increased economic, market and business uncertainty.

In our study we provide a more granular picture of the issue at hand by measuring the extent to which different oil price volatility measures affect systemic risk. We note that various measures exist for oil price volatility. Here, we initially consider three popular measures; namely, the realized, the conditional, as well as, the implied oil price volatility. Both realized and conditional volatility are current-looking measures of volatility, whereas the implied oil price volatility is a forward-looking

[1] Some recent studies include, Gupta and Krishnamurti (2018); Christoffersen and Pan (2018); Gong et al. (2020). In addition, Degiannakis et al. (2018) provide an extensive review of the related literature.

measure. According to authors such as Andersen et al. (2003) and Hansen and Lunde (2006), realized volatility is the most accurate way to make predictions; nonetheless, we opine that all three measures can be employed for both baseline and robustness analysis.

We should also note that Kilian (2009) shows that oil price movements can be driven by aggregate demand shocks, oil supply-side shocks and idiosyncratic (or precautionary demand) shocks. According to this view, positive aggregate demand shocks are expected to have a positive impact on the economy (i.e., oil price soars during periods of extensive economic development), while both the negative oil supply-side shocks and positive idiosyncratic shocks should leave a rather negative economic imprint as they are linked to either interruptions or unanticipated shortages of crude oil in the market. In terms of their impact on financial markets, positive aggregate demand shocks are associated with higher stock market returns, whereas by contrast, both negative oil supply-side shocks and positive idiosyncratic shocks result in downward price pressures in financial markets. The relevant oil price shocks-stock market literature indeed shows the differentiating effects of the former compared to the latter (see, Degiannakis et al., 2018, for a review of the related literature). Motivated by these differentiating effects of oil price shocks in the wider economy and the financial markets, we also assess whether systemic risk responds differently to the alternative oil price volatility shocks.

It should be also mentioned that although some empirical studies focus on the impact of oil price volatility on financial markets, only few studies actually consider the particular link using firm-level or industry-level data (see indicatively, Bams et al., 2017; Joo and Park, 2021) and none of these studies consider the effects of the different oil price volatility shocks on systemic risk. At a very disaggregated level, we consider different types of systemic risk, as well as, different types of oil price volatility and we also accentuate the relevant disparities across different types of industries.

Some studies, though, are related to the systemic risk which is the focal point of the present study. In this regard, these studies are associated with our motivation and therefore are worth mentioning at this point. For example, Reboredo (2015) looks into the impact of oil prices on the financial performance of renewable energy companies and reaches the conclusion that oil price developments play an important role when it comes to the systemic risk of this particular sector. Furthermore, Mensi et al. (2017) investigate systemic risk spillovers between four major stock markets and oil returns and report that, there exists strong dynamic tail dependence, with oil exerting a stronger systemic effect on all four stock markets both in the short- and the long-run. More recently, a conceptually similar study by Ouyang et al. (2022) examines the effect of oil price shocks on systemic risk and finds that negative oil price shocks have a negative impact on systemic risk which is greater than the positive impact generated by positive oil price shocks. The authors also report that the impact of both positive and negative oil price shocks appears to be reduced during the COVID-19 pandemic.

Therefore, motivated by the recent financialisation of oil, as well as, by the strengthening of the nexus between oil and financial markets, we purport to evaluate the impact of different oil price volatility measures on the systemic risk in the US. The contribution of this study is threefold. First, by considering all different types of oil price volatility, we deviate from previous literature in that we investigate a broader spectrum of potential interaction between oil and financial markets. Second, considering the importance of energy price risk on the wider economy, we provide a useful analytical framework for regulators and market participants aiming to acquire a better understanding of said interaction – particularly, in the light of recently adopted climate change mitigation policies. That is, the recent effort at a global scale for a successful transition from CO2-intensifying business activity towards cleaner production practices, renders cost of energy (and its volatility) at the heart of business performance and hence its survival or failure. Third, from the standpoint of empirical methods, by focusing on risk and looking into the impact from different oil price volatility shocks, we extend the framework initially developed by Kilian (2009) who focused on different types of oil price (rather than volatility) shocks. Overall, our study provides new evidence on the ongoing discussion between oil price volatility and financial markets.

Main findings indicate a positive and significant risk exposure of the US firms' systemic risk measures to different types of oil price volatility measures (conditional, realized, and implied). However, the disaggregation of oil price volatility into three different shocks, i.e., supply-driven, demand-driven, and idiosyncratically driven, shows that demand-driven oil price volatility shocks lead to systemic risk increases, whereas supply-driven, and idiosyncratically-driven oil price volatility shocks reduce systemic risk. In addition, our industry analysis lends support to our baseline findings. Moreover, our time-varying analysis implies that our results remain robust when we consider the relationship between different types of oil price volatility shocks and systemic risk at each point in time, including recent developments in the US oil market. Additional analysis shows similar responses from other risk measures (unsystematic, systematic, and total) to oil price volatility measures and shocks. Finally, portfolio analysis shows robust results and highlights the firm size and systematic risk as factors to generate systemic risks in the face of oil price volatility shocks.

The remainder of the paper is organised as follows. Section 2 describes the employed data and presents the construction of the oil price volatility, systemic risk measures and also the empirical methods. Then, the empirical findings are presented, interpreted, along with various robustness checks in Section 3. Finally, Section 4 concludes the study and provides recommendations and policy implications.

2 Dataset and methodology description

2.1 Sample

Our sample covers all NYSE and NASDAQ stocks on the Compustat from 1990 to 2020. To be included, a firm is required to have available balance sheet items via Compustat. Initially, we download the daily stock returns of all available stocks. We find 11,448 firms with over 25 million daily observations. Then, we construct monthly risk measures. We choose a monthly frequency in our analysis for two main reasons. First, oil price volatility shocks can only be estimated in monthly frequency, and second firm risk measures need an adequate time horizon to be robustly calculated. For this reason, we drop the year 1990 from our analysis as the first year of each firm is used for the rolling window calculations. Overall, our sample spans across 11 industries for 30 years, while it is also unbalanced (See Table 1). Hence, our final data-set contains 1,105,265 firm-month observations.

[PLEASE INSERT Table 1 HERE]

All firm financial data have been downloaded from Compustat. The five factors for the US market, needed for the capital asset pricing models, are obtained from Kenneth R. French website. Oil related data have been retrieved from EIA[2], and finally macroeconomic data have been extracted from either FRED or OECD databases. Table A1 shows the variables definitions and the sources of data.

2.2 Oil price volatility estimates

In this subsection, we present the different oil price volatility measures that we employ in the study. Initially, we consider two current-looking measures, namely the conditional and realized oil price

[2]The implied oil price volatility index (OVX) data are extracted from Bloomberg. This index is available from the Chicago Board Options Exchange (CBOE) since May 2007. We indicate that the inclusion of the OVX reduces our sample period and this is the reason of having 521,885 monthly observations when this index is employed. Potentially, the inclusion of this index does not capture events that took place prior to May 2007 and affected the oil market.

volatility, and the forward-looking oil price volatility measure, which is the implied volatility index, OVX. Subsequently, we distinguish the source of oil price volatility, using Kilian (2009) methodology, into supply-driven, demand-driven and idiosyncratically-driven. All three volatility measures, as well as, the oil price volatility shocks are reported in monthly frequency for the period January 1991 until December 2020.

For the estimation of the monthly conditional and realized volatility, we use the daily WTI crude oil prices for the period 2 January 1991 until 31 December 2020. To estimate the oil price volatility shocks we further employ monthly data for the world oil production and Kilian's global economic activity index. The OVX is available from the CBOE and it is also expressed in monthly frequency.

2.2.1 Realized oil price volatility

Motivated by Andersen et al. (2003), the monthly realized oil price volatility is calculated as the squared root of the sum of the daily squared oil price returns for any given month, as follows:

$$OILRV_t = 100\sqrt{12\sum_{s=1}^{S}(oilp_{t,s} - oilp_{t,s-1})^2}, \tag{1}$$

where $oilp$ denotes the WTI oil log-prices and S denotes the number of days (s) in any given month (t).

2.2.2 Conditional oil price volatility

Regarding the monthly conditional oil price volatility, we employ a GARCH(1,1) model, which allows us to estimate the conditional variance, $\sigma^2_{t,s}$, of day s for any given month t. Having estimated the daily conditional variance of oil prices ($\sigma^2_{t,s}$), we compute the annualised monthly conditional volatility, as follows:

$$OILCV_t = 100\sqrt{12\sum_{s=1}^{S}\sigma^2_{t,s}} \tag{2}$$

2.2.3 Oil price volatility shocks

Having estimated the monthly oil price volatility estimates, we employ the Structural VAR model by Kilian (2009) so as to identify the sources of volatility, as aforementioned. The Structural VAR model of order p takes the following general form:

$$\mathbf{A}_0\mathbf{y}_t = \mathbf{c}_0 + \sum\nolimits_{i=1}^{p}\mathbf{A}_i\mathbf{y}_{t-i} + \varepsilon_t, \tag{3}$$

where $\mathbf{y}_t$ denotes the vector of endogenous variables, which are ordered as follows, world oil production, Kilian's global economic activity index and the oil price volatility. A_0 represents the

$N \times N$ contemporaneous matrix and A_i denotes the $N \times N$ autoregressive coefficient matrices. The structural disturbances are denoted by the ε_t, and they are assumed to have zero covariance and to be serially uncorrelated. Hence, the variance-covariance matrix of these structural disturbances is of the following form:

$$E[\varepsilon_t \varepsilon_t'] = \mathbf{D} = \begin{bmatrix} \sigma_1^2 & 0 & 0 \\ 0 & \sigma_2^2 & 0 \\ 0 & 0 & \sigma_3^2 \end{bmatrix}. \tag{4}$$

The reduced form of the Structural VAR model (3) is obtained by multiplying both sides by $\mathbf{A}_0^{-1}$, such as that:

$$\mathbf{y}_t = \mathbf{a}_0 + \sum_{i=1}^{p} \mathbf{B}_i \mathbf{y}_{t-i} + \mathbf{e}_t \tag{5}$$

where $\mathbf{a}_0 = \mathbf{A}_0^{-1} \mathbf{c}_0$, $\mathbf{B}_i = \mathbf{A}_0^{-1} \mathbf{A}_i$, and $\mathbf{e}_t = \mathbf{A}_0^{-1} \varepsilon_t$, i.e., $\varepsilon_t = \mathbf{A}_0 \mathbf{e}_t$. Note that the $\mathbf{e}_t$ are linear combinations of the ε_t, with a variance-covariance matrix of the form $E[\mathbf{e}_t \mathbf{e}_t'] = \mathbf{A}_0^{-1} \mathbf{D} \mathbf{A}_0^{-1'}$.

In order to identify the structural disturbances, we are motivated by Kilian and Park (2009) and we impose the following short-run restrictions on $\mathbf{A}_0^{-1}$:

$$\begin{bmatrix} e_{1,t}^{\Delta \text{World Oil Production}} \\ e_{2,t}^{\text{Global Economic Activity Index}} \\ e_{3,t}^{\text{Oil Price Volatility}} \end{bmatrix} = \begin{bmatrix} \alpha_{11} & 0 & 0 \\ \alpha_{21} & \alpha_{22} & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} \end{bmatrix} \times \begin{bmatrix} \varepsilon_{1,t}^{SSV} \\ \varepsilon_{2,t}^{ADV} \\ \varepsilon_{3,t}^{IDV} \end{bmatrix}, \tag{6}$$

where SSV is the the supply–side driven volatility, ADV is the demand–side driven volatility and IDV is the idiosyncratically-driven volatility. More specifically, world oil production may not respond contemporaneously to shocks in Kilian's global economic activity index and changes in oil price volatility. In addition, Kilian's global economic activity index may not react instantaneously to changes in oil price volatility. Furthermore, world oil production is only contemporaneously affected by supply-side shocks, whereas Kilian's global economic activity index is instantaneously affected by supply-side shocks, and demand-side shocks. Finally, all types of shocks are allowed to contemporaneously influence changes in oil price volatility.

Overall, we mention that we have identified the oil price volatility shocks for all three volatility measures, yet for brevity we only report those from the oil conditional volatility in the section of empirical results.

Figure 1 plots the visual representation of the three oil price volatility shocks. We initially focus on supply-side and the most prominent patterns. Thus, we observe a significant contribution of the supply-side to the oil price volatility during the first decade of our sample period, which is associated with Iraq's invasion of Kuwait, the first war in Iraq by the US, as well as, various OPEC cuts in production, which led oil prices in higher levels. Then, we notice two further SSV peaks during the second US war in Iraq in 2003 and the oil price slump of 2016. Overall, we note that supply-side driven oil price volatility shocks are typically associated with geopolitical unrest and OPEC's decisions related to production quotas.

Turning our attention to the most noticeable patterns of oil price volatility shocks related to demand-side, we report the continues decrease of ADV since 2002 until 2007, which is a period associated by the unanticipated growth in demand for industrial commodities, including oil, by the emerging economies and especially China. Furthermore, we witness a peak of the ADV during 2014, which marked the end of a prolonged period when oil prices fluctuated between \$80 and \$100, during which the global economy was recovering from the global financial crisis. We argue that demand-side driven oil price volatility shocks are naturally originate in periods of economic boom or recessions.

Finally, the patterns for the idiosyncratically-driven oil price volatility shocks are mostly indicative of a persistent downward trend that reached a trough after the Great Recession. Furthermore, we observe that the main driver of oil price volatility during the period of the coronavirus outbreak in 2020 and the associated oil price crash is the IDV rather than the demand-driven or supply-driven shocks.

Overall, the visual representation of the three oil price volatility shocks and the theoretical background that supports the patterns, provides evidence that abrupt declines in oil prices are accompanying with higher values of oil price volatility and vice versa.

[PLEASE INSERT Figure 1 ABOUT HERE]

2.3 Systemic risk measures

Our main measure of systemic risk is the $\Delta CoVaR$. Systemic risk is defined as the contribution of Value at Risk (VaR) of one firm to the Value at Risk of the industry, in which this firm operates. For example, the extent to which British Petroleum Company PLC under distress can transmit instabilities to the whole Oil & Gas sector. In this study, a firm under distress is reflected on the 95% of the losses distribution. This part of the distribution represents the highest daily expected losses, which can easily be computed through the traditional VaR method. An alternative procedure to control for VaR, which is robust to outliers' spillover effects and is directly associated with systemic risk, is proposed by Adrian and Brunnermeier (2016):

$$Pr(X_j|C(X_i) \leq CoVaR^q_{j|C(X_i)}) = q, \tag{7}$$

where X_j is the industry return losses ($X_j = R_j^{-1}$) conditional on the losses of a particular firm i ($X_i = R_i^{-1}$) at any part of the distribution (i.e., $q = 95\%$). Moreover, $CoVaR_{j|C(X_i)}$ is the Value at Risk of the industry j conditional on some event $C(X_i)$ of institution i. In this regard, $CoVaR$ can be implicitly estimated by running the following quantile regression:

$$X^q_{j,t} = a^q + \beta^q X_{i,t} + B^q M_{t-1} + u^q_{i,t}, \qquad q \in (0,1), \tag{8}$$

where the predictive values of $X^q_{j,t}$ are the Value at Risk of financial system conditional on $X_{i,t}$ at month (t). M_{t-1} is a vector that contains important macroeconomic variables lagged 1 period behind to capture the overall investment climate. Following Adrian and Brunnermeier (2016), we include market return losses ($X_m = R_m^{-1}$), the short-term market volatility and the daily yield from the US 10-year bond. Therefore, $CoVaR^q_{i,t} = \widehat{X}^q_{j,t}$ and $CoVaR^q_{i,t}$ is the VaR of j conditional on VaR of i at any q and t given. Additionally, to demonstrate a more effectively approximate systemic risk, we use the $\Delta CoVaR$ measure, which is the change in $CoVaR$ of institution i at $q = 95\%$ to its median state ($q = 50\%$). The median state of any institution can be estimated by running the Equation 8 at $q = 50\%$ and then saving its fitted values ($CoVaR^{0.50}_{i,t}$). In other words, we run Equation 8 twice at q=95% and at q=50%, and save the fitted values. Then, $\Delta CoVaR$ can be measured as shown in

Equation 9:

$$\Delta CoVaR_{i,t} = CoVaR_{i,t}^{0.95} - CoVaR_{i,t}^{0.50}. \tag{9}$$

As a robustness, we use an alternative systemic risk measure, the Marginal Expected Shortfall (MES). Acharya et al. (2017) define MES as short-run expected equity loss conditional on the market taking a loss greater than its Value-at-Risk at $1-q$ (i.e., 5%). Practically, MES can be measured by estimating firm i's losses when the market j as a whole is under distress. The MES reads:

$$MES_{i,t} \equiv -E_t(R_{i,t} | R_{j,t} \leq -VaR^{0.05}) \tag{10}$$

where $R_{i,t}$ and $R_{j,t}$ the stock returns of the firm and market, respectively. $-VaR^{1-q}$ is a constant corresponding to our tail risk, which is chosen at 5% level in line with other studies (e.g., Raykov, 2022).

Figure 2 illustrates the evolution of the $\Delta CoVaR$ and MES types of systemic risks. Specifically, it shows the impact of the GFC of 2007-08 which is associated with a sharp increase for both types. It is worth noting that during this episode, the failure of large investment US banks such as the Lehman Brothers, posed substantial systemic risks. A notable observation is also related to the impact of coronavirus pandemic which reflects a sharp upward trend. In this respect, a large systemic risk suggests a great speed of the coronavirus spread according to which a failure of one firm might cause the failure of many.

[PLEASE INSERT Figure 2 ABOUT HERE]

2.4 Theoretical transmission channels

All three measures of oil price volatility (OILRV, OILCV, OVX) are expected to affect the systemic risk positively. Higher level of uncertainty in the oil market should be translated into higher levels of financial instability. Nevertheless, we posit that distinguishing between the different types of oil price volatility provides a more accurate picture of the interaction, uncovering hidden relationships among the variables of interest.

As mentioned in Section 1, motivated by Kilian (2009) who disentangles oil price changes into three shocks, namely, supply-side, aggregate demand and idiosyncratic (or precautionary), we also perform an equivalent analysis, albeit in oil price volatility.

In particular, a positive supply-side development in the oil market such as technological advances in drilling which increases the oil supply is expected to reduce the price of oil. In response, oil price volatility associated with supply-side (SSV) rises, where firms benefit from such oil price decrease and thus they face less risks. So, we argue that a positive change in the world oil production is regarded as positive news for the corporate sector, and albeit the higher oil price volatility, leads to lower systemic risk.

Equivalently, a negative demand-side development such as decreasing demand for industrial commodities including oil, is expected to reduce economic activity and push financial markets to lower levels. In turn, oil price volatility associated with demand-side (ADV) increases, and systemic risk rises. We claim that a negative oil demand-side episode suggests that there is weak and unstable global economic activity, which is associated with smaller business opportunities and hence, greater financial risk.

Finally, a negative idiosyncratic episode such as reducing fears about future oil supply shortfalls and hence greater availability of oil for current use is expected to drive the oil price to fall. In response, oil price volatility associated with idiosyncratic-side (IDV) increases, yet systemic risk is expected to fall. We mention that as a negative idiosyncratic shock lowers the uncertainty about the future availability of oil, which in turn reduces the uncertainty in the economy, creates a stable business environment and consequently leads to lower financial risk.

Overall, the aforementioned positive or negative episodes in the oil market move oil prices in the same direction (a fall) and oil price volatility (in terms of SSV, ADV, and IDV) in the opposite direction (a rise). Then, depending on the status of the economic activity (stable or unstable) that these shocks generate, we argue upon the impact on the firm's systemic risk (lower or higher). Our expectations on the responses of systemic risk to oil price volatility are summarised in Table 2.

[PLEASE INSERT Table 2 ABOUT HERE]

2.5 Descriptive Statistics

Table 3 reports the descriptive statistics of our variables. Starting with the oil-specific variables, the forward-looking implied volatility (OVX) appears to have a higher mean value and volatility than the current-looking volatility measures (i.e., OILRV and OILCV), as expected. Typically a higher implied volatility value compared to the realized volatility indicates risk aversion in the market. Furthermore, implied volatility tends to be more volatile given that it incorporates expectations about rare events (which may not occur), whereas in the current-looking volatility measures such events are not incorporated in the estimation unless they have been materialized. On the other hand, the two current-looking volatilities share similar characteristics.

Regarding the oil price volatility shocks, it is evident that the idiosyncratic oil price volatility (IDV) is more volatile than supply-side (SSV) and demand-side (ADV) oil price volatility shocks. This can be attributed to the fact that idiosyncratic shocks are uncertainty shocks primarily generated by geopolitical turmoil, as well as, decisions made by money managers that participate in the oil market.

With reference to the stock market variables of $\Delta CoVaR$ and MES, they exhibit a leptokurtic distribution and positive skewness, as expected. In this regard, we notice that a long-right tail is indicative of a sluggish increase and a speedy decline. In addition, turning to the control variables which we explain in detail in the following paragraph, we report similar properties.

For firm-level control variables we use firm size (log of total assets, LNTA), leverage (LEV), earnings per share (EPS), dividend yield (DVY), book-to-market (B/M), liquidity ratio (LIQ), and the log of trading volume (LNVOLUME). Then, for macro-level data, we consider the TED spread (TED), volatility index (VIX), investment sentiment (CREDIT), consumer confidence index (CCI) and business confidence index (BCI). A detailed explanation of the variables can be found in Table A1.

We include firm size as prior literature has shown that larger firms are better equipped to deal with systemic risk. We also control for variables that are found to explain high variation of the capital asset models, such as the previously mentioned firm-level variables. In addition to this, our macro variables are able to capture the fear in the market, the investment sentiment, the consumer sentiment, the business sentiment and consequently the overall economic climate. We also control for the time to capture different events in our long estimation period, and we also consider that different sectors have different risk levels.

[PLEASE INSERT Table 3 ABOUT HERE]

3 Empirical Findings

3.1 Baseline Results on Systemic Risk

Our baseline regressions test the relationship between oil-specific variables (i.e., different types of oil price volatility and different types of oil price volatility shocks) on systemic risk, using the following specification:

$$y_{i,t} = a + \beta' X_{i,t} + \gamma' Z_{i,t} + \Lambda + \varepsilon_{i,t}, \tag{11}$$

where y is one of the systemic risk variables ($\Delta CoVaR$, MES), X shows the oil price volatility shock variables (SSV, ADV and IDV), while we separately test for the oil realized (OILRV) and conditional (OILCV) volatility as well as the implied volatility (OVX). In addition, Z is a vector that controls for various firm-specific and macro-level characteristics. Finally, Λ shows different specifications controlling for firm, industry, month, year and industry-by-month-by-year fixed effects. Finally, we cluster standard errors by firm.

We use standardised variables to obtain better distributional properties, to reduce the impact of outliers and thus to have more meaningful coefficients. We have standardised the risk measures and oil-specific measures to zero unity space. If control variables are not expressed in either ratio or a percentage, we use natural logarithms.

In this regard, Tables 4-5 summarise our baseline results. In particular, we note that each Table consists of seven columns. Left columns start with very general specifications (i.e., 1, 2 and 3) which are all related to the three types of oil price volatility and as we move to the right columns (i.e., 4, 5, 6 and 7) which are all associated with the three types of oil price volatility shocks our specifications become more restricted. Therefore, we follow a two step approach within each Table. More specifically, the first step is associated with the three types of oil price volatility such as realized, conditional and implied. We attempt to investigate their impact on systemic risk factors. For the second step, we seek to identify the specific sources of oil price volatility. In other words, to examine whether they are driven by supply and demand events in the oil market. On a final note, it should be mentioned that the second step analysis is only related to the conditional volatility measure.[3]

Our main results, with $\Delta CoVaR$ as a dependent variable, are reported in Table 4. The findings in columns 1, 2, and 3, show that the effects do not differentiate among the different types of oil price volatility, as positive and significant effects are reported. More importantly, we show that disentangling oil price volatility into its three shocks, uncovers these hidden relationships that we referred to in Section 2.4. To be more explicit, SSV and IDV trigger negative and significant responses to the $\Delta CoVaR$, whereas the reverse holds true for the ADV. Furthermore, we observe that the estimated coefficients demonstrate large values, which is indicative of the greater ability of oil price volatility shocks to influence systemic risk. We also notice that all specifications in Table 4 appear to report high R^2 values. Arguably, this finding underlines that oil price volatility shocks have the ability to cause episodes in financial stability.

[PLEASE INSERT Table 4 ABOUT HERE]

Subsequently, we assess whether results remain similar when the MES is used as dependent variable.

[3]For brevity, we present only the baseline findings related to oil conditional volatility. We mention that the baseline results for the realized and implied volatility are qualitatively similar and further available upon request.

The findings are reported in Table 5. Even in the case of MES, we can observe that the SSV and IDV exercise a negative and significant effect on systemic risk, whereas the latter is positively impacted by the ADV. Thus, the baseline results shown in Table 4 and Table 5 remain qualitatively similar and thus we confirm our argument regarding the link between oil price volatility and systemic risk.

[PLEASE INSERT Table 5 ABOUT HERE]

In retrospect, we argue that systemic risk behaviour is dependent on the type of the oil price volatility shock. Given that the uncertainty surrounding the oil market is considered as a major source of endogenous or exogenous shock (depending on the industry), it has the potential to trigger simultaneous firm failures, leading to economic and financial instability. Nevertheless, our findings show that higher oil price volatility does not necessarily lead to greater systemic risk, as the source of oil price volatility matters. Such findings has not been previously reported by the related literature.

It would be instructive at this point to note that the baseline analysis refers to the total number of firms (energy and non-energy). In addition, our sample contains both oil users and non-oil users. Therefore, it deserves to re-estimate our baseline results excluding the energy firms, which are expected to respond in a higher magnitude, as well as, splitting our sample between oil and non-oil users. Such analysis will provide additional insights as to whether different types of firms respond to oil price volatility shocks in a similar fashion or whether heterogeneous responses exist. We discuss this analysis in a greater detail in the industry analysis section, which serves as our first robustness test.

3.2 Industry analysis

To perform an industry analysis, the first step is to exclude energy firms from the baseline analysis. As already mentioned, this choice is motivated by the fact that energy firms may influence the estimated coefficients that we reported thus far. Table 6 reports the results which are related to the total sample period. Evidently, we note that the findings for all specifications tend to be consistent with those reported in Table 4 and Table 5, in terms of the expected signs and significance.

In Table 6 we also separate industries into (i) oil users and (ii) non-oil users. Following Kilian and Park (2009), this motivation is attributed to the fact that we expect heterogeneous responses at the industry level to oil price volatility shocks since the degree of sensitivity varies across industries. Thus, it is not surprising to anticipate that oil price volatility shocks will exert different effects on different industries. Interestingly enough, we do not find any material difference between the oil and non-oil users. Irrespectively of the type of firms, results show that SSV and IDV leads to lower systemic risk, whereas ADV aggravates it. This holds for both measures of systemic risk that we consider in this study. Hence, even the sub-samples of firms that are reported in Table 6 strengthen our main findings, that is that the impact of oil price volatility on systemic risk depends on the source of the volatility.

Our findings are somewhat in line with the evidence provided by Reboredo (2015), who reports that oil price dynamics (although the study does not focus on volatility) appear to exert around a 30 percent impact on the systemic risk of firms, with a particular focus on the renewable energy industry.

[PLEASE INSERT Table 6 ABOUT HERE]

In the following section we perform alternative tests in order to satisfy the robustness of our results.

3.3 Time Varying Estimations

An additional robustness test is related to the time-varying estimations using a rolling window approach. In a rolling regression the sample is dynamic over a given window and not fixed over the entire examined period. Empirically, the length of this window is often somewhere between 24 and 60 months, while there is some burning period (i.e., 30 months) in order to reach adequate number of observations, and so estimations to be statistically valid. The chosen window is shifted month by month over the entire sample period. From an econometric point of view, the use of rolling windows causes a sub-optimal use of the data by picking an ad hoc window size rather than an optimal full sample. However, rolling window regressions can effectively capture short-term dynamic impacts of oil shocks on firm level, while controlling for various shocks that happened during these periods. We obtain monthly sample estimates of beta from rolling regressions. We use a 60 month estimation window to obtain timely estimates that pick up short-term fluctuations in betas[4]. We estimate rolling sample betas by running the following time-series regression (Dangl and Halling, 2012; Cosemans et al., 2016):

$$y_{i,t,s} = a_t + \beta_{i,t} V_{i,t,s} + \epsilon_{i,t,s}, \tag{12}$$

where $y_{i,t,s}$ is the different firm risks and $V \equiv (X, Z, \Lambda)'$ is a vector that contains explanatory variables, including the oil shocks similar to Equation 11. The subscript s=(1,2,...,τ) is used to index the y before the end of month τ and τ is the length of the estimation window, that is, τ=60 months. The subscript τ is used to emphasise that we estimate integrated betas for each time using a rolling window of monthly data. The regression slope $\beta_{i,t}$ is our object of interest.

Figure 3 depicts the time-varying effects for $\Delta CoVaR$. Furthermore, it reports the percentage of firms that are impacted by each oil price volatility shock at each time point.

[PLEASE INSERT Figure 3 ABOUT HERE]

On the whole, we observe that SSV maintains its negative impact on systemic risk. More importantly, though, we observe that firms are susceptible to such oil price volatility shocks only in certain time periods, such as the early 2000s, 2016 and in the early COVID-19 pandemic period. Hence, the SSV is more prevalent during periods of exogenous shocks, such as geopolitical tensions and the pandemic.

Turning to the demand-side oil price volatility shocks, we show that the ADV coefficient is mainly positive and that its impact on systemic risk of firms is mostly experienced during economic crises, when most firms within our sample are affected. Finally, as far as the IDV is concerned, we report that its main negative effect on systemic risk appears in the period immediately after the GFC of 2007-08.

Overall, the time-varying analysis allows us to extend our key findings, since, on one hand, it confirms the baseline results from Table 4 and Table 5, yet, on the other hand, it further shows that these impacts are observed at different time periods.

Figure 3 further includes the periods when important developments occurred in the US oil market. In particular, the green lines mark the beginning of (i) the US shale oil revolution, when technological advances in drilling from tight wells contributed to increasing oil production in the US since 2007; (ii) the new US oil transport infrastructure in 2012, when new pipeline, rail and barge projects enabled crude oil to flow to and from the Gulf of Mexico more easily; and (iii) the lift of the US federal export ban by the Congress in December 2015. These developments allowed greater US oil production and exports, which were beneficial for the US economy. It is rather interesting to note that since these

[4] Alternative window lengths do not alter the main findings.

developments took place, the impact of SSV and IDV on systemic risk diminishes. This is a rather important finding, given the fact that these oil market developments in the US focus on the supply-side. Hence, such events should be anticipated to reduce the exposure of firms' systemic risk on oil price volatility shocks driven either by the supply-side or the uncertainty about the future availability of oil.

3.4 Further Results on Firm Risks

Thus far the findings convincingly show that oil price volatility matters for systemic risk, but more importantly we find that the source of volatility (demand or supply) is an important factor that contributes to our understanding on the link between the former and firms' systemic risk. Nevertheless, given that firms face other different types of risks (such as systematic and unsystematic), it would be an omission of this study not to provide at least some insights on the impact of oil price volatility on these risks.

Regarding these firm risk measures, we consider the unsystematic, systematic and total risk. For all these risks, we have to compute the daily stock return as: $R_{i,s} = ln(Price_{i,s}) - ln(Price_{i,s-1})$, where i is the firm and s is the day.

First, to construct the unsystematic and systematic risk, we follow the capital asset pricing models, such as the three-factor (Fama and French, 1993) and the four-factor (Carhart, 1997) models which have been extensively used in the empirical literature (Ang et al., 2006, 2009). We build our approach on the comprehensive five-factor capital asset pricing model following Fama and French (2015):

$$R_{i,s} - R_{f,s} = \alpha_i + \beta_{i,1}(R_{m,s} - R_{f,s}) + \beta_{i,2} SMB_s + \beta_{i,3} HML_s + \beta_{i,4} RMW_s + \beta_{i,5} CMA_s + u_{i,s}, \quad (13)$$

where the left part of the equation corresponds to the excess stock return [(daily stock return ($R_{i,s}$) minus daily risk free rate ($R_{f,s}$)], while the right part consists of the (α_i) which shows the performance of a stock relative to the market portfolio, the first factor ($R_{m,s} - R_{f,s}$) which is the excess return on the market portfolio, the second factor (SMB_s) which measures the return of small over large stocks, the third factor (HML_s) which represents the return of value stocks over growth stocks, the fourth factor (RMW_s) which reflects the difference of stock returns between robust and weak profitability firms, the fifth factor (CMA_s) which signifies the return of low over high investment firms and $u_{i,s}$ denotes the residuals. We next run time series rolling window (251 days) regressions to Equation (13) by assuming that the residuals are normally distributed with zero mean and constant variance.

In terms of the unsystematic risk (UNS), we follow previous studies (e.g., Ferreira and Laux, 2007; Duan and Wei, 2009) that define unsystematic risk as the standard deviation of the residuals of the pricing models. Thus, from Equation 13, we retain the residuals. Then, we take the average of a rolling window standard deviation of the residuals:

$$UNS_{i,t} = 100\sqrt{\frac{\sum_{s=1}^{S} \sigma(u_{i,s})^2}{S}} \times \sqrt{K}, \quad (14)$$

where i is the firm, t is the month, K corresponds to trading days of a year with $K \approx 251$, s represents the days of each month, and S shows the total days of every month which is approximately 22 days.

In terms of the systematic risk (BETA), we are interested in the coefficient ($\beta_{i,1}$), which corresponds to the systematic risk. As this is rolling window regressions, our procedure yields one ($\beta_{i,1}$) coefficient for every day. Following Duan and Wei (2009), we average the daily betas and thus we can obtain our monthly systematic risk:

$$BETA_{i,t} = \frac{\sum_{s=1}^{S} \beta_{i,1}}{S}. \quad (15)$$

Moreover, we compute the total risk (TR), which includes both systematic and unsystematic risk elements and can be measured as the annualized standard deviation of the daily stock returns. However, we would like to have the monthly total risk and therefore we estimate the average rolling window standard deviation, in line with Ilhan et al. (2021), for any month given:

$$TR_{i,t} = 100\sqrt{\frac{\sum_{s=1}^{S} \sigma(R_{i,s})^2}{S}} \times \sqrt{K}. \quad (16)$$

In other words, total risk is the average rolling window standard deviation of all days for each month.

Figure A1 at the Appendix shows the evolution of the three firm risks. A notable observation is the significant peak and trough of the total risk during 2000 and 2004-2005 respectively. More specifically, the significant peak is related to the dotcom bubble, an internet-based rising business during 1995-early 2000 which started to collapse in March 2000 and led to bankruptcy many technology and online related US firms. This negative impact was also evident in the market performance of the NASDAQ Composite index which erased all its previous years gains. As regards the significant trough, this is related to the pre-GFC of 2007-08 which was characterised by economic growth, falling unemployment and low inflation. In this regard, the rise in housing prices and the boom in the housing industry was supported by a rise in consumer and business confidence and the growth in bank lending due to the surplus of liquidity.

Table 7 reports results for the Unsystematic Risk (UNS). The results in columns 1, 2, and 3, confirm our anticipation of a positive impact of the three oil price volatility measures on Unsystematic Risk, albeit it is only statistically significant for the OVX measure. Turning to the oil price volatility shocks, our findings are consistent with the initial expectations showing that SSV (without the inclusion of the control variables) and IDV exhibit a negative impact on UNS, whereas the reverse holds true for the ADV. Nevertheless, we cannot report a significant impact of SSV and ADV on UNS. Indeed, regardless of the fact that we include or exclude our control variables, the coefficients of SSV and ADV in columns 4, 5, 6 and 7 do not appear to be significant predictors of the Unsystematic Risk. A plausible explanation can be attributed to the fact that SSV (generated by unexpected changes in global supply of crude oil) and ADV (generated by unexpected changes in global business cycle) may not be related to firm-specific risk factors but instead to be regarded as factors that influence the wider US economy. The significant finding is only evident in the case of IDV impact on UNS. A plausible interpretation can be related to the fact that IDV are regarded as idiosyncratic oil price volatility shocks as they refer to uncertainty about the future availability of oil and hence, to firm-specific risk factors and thus they are mostly expected to influence the Unsystematic Risk.

[PLEASE INSERT Table 7 ABOUT HERE]

Table 8 reports results for the Systematic Risk (BETA). Once again, our findings in columns 1, 2, and 3 are in line with our expectation as they provide evidence that the Systematic Risk responds positively and statistically significantly to the three measures of the oil price volatility. Regarding the oil price volatility shocks, we confirm our initial expectation of a positive sign in the case of ADV and further their significant predictive power to influence the Systematic Risk (specifically for the coefficients in columns 5, 6, and 7 which account the control variables). This finding implies that demand-side oil price volatility shocks appear to display macroeconomic implications for the wider US economy. With reference to the IDV, the expected negative sign and significance response are only evident in column 4 which does not account for the control variables. Once again, we argue that IDV are mostly expected to influence the Unsystematic Risk rather than the Systematic Risk. Indeed, our findings in Table 7 confirm our claim regarding the significant impact of IDV on Unsystematic Risk. As regards the SSV, we are unable to support our initial expectation of a negative sign and further there is no evidence to support the importance of SSV in explaining the Systematic Risk. A plausible explanation could lie on evidence related to the fact that SSV appear to play a declining or minor role in the US economy and the financial markets (see, Broadstock and Filis, 2014) and developments are mainly driven by ADV shocks.

[PLEASE INSERT Table 8 ABOUT HERE]

We continue our analysis with Table 9 that reports our results for the Total Risk. Columns 1, 2 and 3 show that all oil price volatility measures have a positive impact on Total Risk, which further confirms our initial expectations. However, when we consider the three oil price volatility shocks, our results further strengthen our expectation that once the driving source of oil price volatility is identified, then the effects on firms risk could be differentiated. On the one hand, SSV (ADV) exhibit the expected negative (positive) sign and their coefficients demonstrate predictive power to influence the Total Risk. Furthermore, IDV shows the expected negative sign and significance in column 4 which does not account for the control variables. As Total Risk represents the aggregate of both systematic and unsystematic risks, then it is somewhat expected that our results show a stronger impact from supply-side and demand-side oil price volatility shocks and a weaker impact from idiosyncratic oil price volatility shocks. This interpretation accords with our previous findings in Table 7 and Table 8.

[PLEASE INSERT Table 9 ABOUT HERE]

3.5 Portfolio Analysis

Having established that oil price volatility shocks primarily matter for systemic, as well as, for other types of firm risk, we proceed with a final set of results, based on a portfolio analysis. According to both theoretical and empirical predictions, large and high volatility firms are sources of systemic risk (Adrian and Brunnermeier, 2016; Fernholz and Koch, 2017; Hagendorff et al., 2018; Varotto and Zhao, 2018). Several studies (e.g., Acharya et al., 2017; Löffler and Raupach, 2018) discussed the connection between systematic and systemic risk. It is evident that a systematic risk can sufficiently jeopardise financial stability. In parallel, Acharya et al. (2012); Benoit et al. (2017) underline that unsystematic risk is a result of correlated investments, which in turn causes contagion in the financial system. Therefore, firm-specific shocks can have significant macroeconomic consequences, and therefore harm financial stability. Based on this notion, we are splitting our sample across portfolios with different sizes and risk levels. Particularly, we consider size as well as unsystematic and systematic risk portfolios. Arguably, it would be interesting to investigate the channels through which oil price volatility shocks transmit systemic risk shocks to the financial system.

[PLEASE INSERT Table 10 ABOUT HERE]

In Table 10 we form quantile portfolios by virtue of (i) small to large firm size in Panel A, (ii) low to high unsystematic risk in Panel B, as well as (iii), low to high systematic risk in Panel C, and we examine the effects of oil price volatility shocks on systemic risk. For each month, we sort firms into quantile portfolios, where 'low' indicates the lower 20% of the firm size, unsystematic and systematic risk distribution. At the other end of the spectrum, 'high' indicates the top 20% of the distribution, while, '2', '3', and '4' portfolios are formed accordingly.

Even though, on the whole, the results in Table 10 confirm our initial findings, it is rather interesting that the magnitude of the effects seems to be different in certain cases, depending on the quantile point. For instance, we observe that for larger firms, which tend to be more interconnected, the ADV and IDV assume their highest values. Even more, we find that systematic risk from firms with the lowest and the highest levels of unsystematic risk seems to be affected the most by the ADV. Finally, SSV seems to assume its highest coefficient on portfolios with the highest level of systematic risk.

Overall, these results suggest that regulators that aim to bring stability to the financial system should not only be interested in the origin of the oil price volatility shock but also on the firm size, as well as, the levels of firm's systematic and unsystematic risk.

4 Conclusion

This empirical paper uses an unbalanced panel data set of over 11,000 US firms for the period from 1991 to 2020 and makes use of monthly data to examine how oil price volatility shocks affect systemic risk. Within the framework of our study, we document that assessing the impact of oil price volatility on systemic risk at an aggregate level cannot uncover the full story. Thus, we emphasise the importance of disentangling oil price volatility shocks by virtue of origin in order to delve deeper into this rather complex relationship.

The main findings document that oil price volatility shocks exert a material impact on measures of systemic risk. Specifically, we provide evidence that supply-driven and idiosyncratically-driven shocks reduce systemic risk, while a demand-driven oil price volatility shock increases systemic risks. Moreover, our results remain qualitatively similar when we perform an industry analysis for energy and non-energy firms, as well as, oil users and non-oil users. Furthermore, our time-varying analysis confirms the important role of geopolitical and economic events as well as oil market developments to influence oil price volatility shocks and consequently systemic risk. What is more, we report that our findings remain consistently robust when we employ alternative risk factors such as unsystematic, systematic and total. Finally, our quantile portfolio analysis confirms our baseline analysis and further stresses the importance of firm size as a factor that affects systemic risk through the different types of oil price volatility shocks.

Our findings have important implications considering the fact that oil price volatility can be regarded as a leading macroeconomic indicator, and thus it conveys significant information in the attention of corporate decision makers, financial market participants and policy makers. More specifically, we refer to implications related to firm valuation, diversification opportunities and portfolio rebalancing, cost of capital, and policy initiatives for systemic risk.

As we show in the study, the different oil price volatility shocks lead to changing levels systemic risk. Hence, the information content advantage which characterises oil price volatility shocks creates initiatives in the attention of policy makers in order to manage and diminish systemic risk and thus, reduce the probability of a financial instability event. More specifically, policy makers should monitor oil price volatility shocks so as to gain time to prepare the responses for the protection of the financial system when such shocks occur in the market.

However, given that oil price volatility shocks also matter for other types of firm risk, there are additional implications that emerge from our study. For instance, corporate managers should be aware of the impact of oil price volatility shocks on systematic and unsystemtic risk, when they estimate their cost of capital or when they proceed to firm valuation estimations. We should not lose sight of the fact that cost of capital and firm valuation methods use firm's risk as their discounting factor. Furthermore, financial market participants tend to rebalance their portfolios or make decisions related to their diversification strategies, based on the different firm risk level. Thus, our findings show that such investment decisions are impacted not only by the level of oil price volatility, but also from the driving source of the latter, given that not all oil price volatility shocks affect the different types of firm risk on the same manner.

A promising area for future research may include additional international financial markets such as the Euro area, and Asian region industrialised economies, whose financial markets also play an important role in the global financial system. Finally, another potential venue for further research would be the more in-depth examination and hence a deeper understanding of the link between oil price volatility shocks and systemic risk. Thus, it would be interesting to further investigate whether early warning systems that timely detect systemic anomalies in relevant industries could be predicated upon developments in the market for oil, which cause shocks to oil price volatility.

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Table 1: Year and Industry sample composition

Notes: [a]In 2020, we did not find many control variables, this is why our sample drops considerably. Firms are allocated to industries based on Global Industry Classification Standard.

Panel A: Year Composition				
Year	N. of firms added	N. of firms left	N. of obs	sample %
1991	297	0	1,009	0.09
1992	357	2	5,912	0.53
1993	761	2	13,000	1.18
1994	627	38	20,858	1.89
1995	676	99	26,771	2.42
1996	908	114	35,588	3.22
1997	609	238	41,439	3.75
1998	558	331	45,438	4.11
1999	926	386	50,409	4.56
2000	572	511	52,455	4.75
2001	318	583	50,482	4.57
2002	225	475	47,516	4.30
2003	224	410	45,270	4.10
2004	313	299	44,848	4.06
2005	266	323	44,457	4.02
2006	293	337	43,800	3.96
2007	321	347	43,424	3.93
2008	137	373	41,726	3.78
2009	146	309	39,520	3.58
2010	303	294	39,209	3.55
2011	293	265	39,404	3.57
2012	384	296	40,465	3.66
2013	403	247	41,721	3.77
2014	401	284	43,224	3.91
2015	265	351	42,698	3.86
2016	185	348	40,938	3.70
2017	243	308	39,941	3.61
2018	223	277	39,461	3.57
2019	203	298	38,327	3.47
2020[a]	11	2801	5,955	0.54
Total	11,448		1,105,265	100.00
Panel B: Industry Composition				
GICS	Industry name	N. of firms	N.of obs	sample %
	Others	190	4,277	0.39
10	Energy	656	59,922	5.42
15	Materials	370	37,274	3.37
20	Industrials	1,124	114,080	10.32
25	Consumer Discretionary	1,515	146,803	13.28
30	Consumer Staples	375	35,937	3.25
35	Health care	1,976	188,140	17.02
40	Financials	2,270	235,092	21.27
45	Information Technology	2,270	210,285	19.03
50	Communication Services	409	35,366	3.20
55	Utilities	67	5,994	0.54
60	Real estate	226	32,095	2.90
Total		11,448	1,105,265	100.00

Table 2: Theoretical Identification

Impact	Channel		Expected coefficient
SSV rises (↑)	Increased oil supply	Drops the oil price	Lower systemic risk (↓)
ADV rises (↑)	Decreased oil demand	Drops the oil price	Higher systemic risk (↑)
IDV rises (↑)	Decreased idiosyncratic demand	Drops the oil price	Lower systemic risk (↓)
SSV drops (↓)	Decreased oil supply	Increases the oil price	Higher systemic risk (↑)
ADV drops (↓)	Increased oil demand	Increases the oil price	Lower systemic risk (↓)
IDV drops (↓)	Increased idiosyncratic demand	Increases the oil price	Higher systemic risk (↑)

Table 3: Descriptive Statistics

Notes: This tables reports the descriptive statistics. Panel A shows the oil related variables. Panel B describes the stock market related variables. Finally, Panel C shows the control variables. Column 1 reports the abbreviation of the variables as described in Table A1. Column 2 shows the available observations. Next columns show the mean, Q1, median and Q3 statistics. Then, the standard deviation, minimum and maximum of the variables are reported. Finally, we report the skewness and kurtosis.

Variable	Obs	Mean	Q1	Median	Q3	Std	Min	Max	Skewness	Kurtosis
Panel A: Oil variables										
OILRV	1,105,265	10.2839	7.2160	9.2129	12.0124	8.2929	3.2080	335.4480	27.3596	1056.6280
OILCV	1,105,265	11.4449	8.5277	10.3290	12.6943	8.5022	4.6050	272.3610	20.4801	576.2548
OVX	521,885	36.2901	28.1110	32.8213	41.3208	13.8559	15.6100	170.5500	2.0933	13.2778
SSV	1,104,265	12.6454	11.8469	12.6212	13.5062	1.3029	8.9537	16.2976	-0.1043	3.2286
ADV	1,104,265	12.5225	8.9865	12.4228	15.3285	6.0423	-5.0740	48.6557	1.2674	8.7874
IDV	1,104,265	12.2414	6.6475	11.3522	17.1643	8.2661	-6.0845	69.7510	1.0180	6.1184
Panel B: Stock market variables										
$\Delta CoVaR$	1,075,733	12.3260	8.6679	10.7543	15.3675	4.7121	4.7832	31.7119	1.3101	5.3761
MES	1,074,777	1.0650	0.0000	0.0000	0.0000	5.6176	-5.2147	39.2829	5.3009	32.4081
Panel C: Control variables										
LNTA	1,105,265	4.8556	3.2570	5.1907	6.7015	2.7246	-6.9078	13.9287	-0.7000	4.1512
LEV	989,062	2.2784	0.1355	0.4561	1.5495	5.6361	0.0045	42.0848	4.9728	31.6373
EPS	993,678	0.1469	-0.4500	0.0000	0.8800	1.8050	-7.1300	6.8000	-0.2194	7.7610
DVY	1,104,560	0.2873	0.0000	0.0000	0.0800	3.0474	0.0000	440.0000	105.2143	14355.5600
B/M	991,614	0.9703	0.3612	0.7222	1.2569	0.9920	0.0000	12.7921	3.2579	20.3488
LIQ	843,697	4.6351	1.0499	1.8863	3.5075	110.4086	-12.7213	24108.0000	177.2683	35634.7500
LNVOLUME	1,088,401	10.8506	9.3372	11.0589	12.5957	2.4617	-3.1355	20.0995	-0.4848	3.4211
TED	1,105,265	0.4758	0.2300	0.3700	0.5800	0.3668	0.1200	3.3500	3.0029	17.5314
VIX	1,105,265	19.8202	13.8400	18.2300	23.9500	7.6492	9.5100	59.8900	1.6377	7.1728
CREDIT	1,105,265	2.4379	1.8400	2.3400	2.8500	0.7507	1.3000	6.1000	1.5707	7.7202
CCI	1,105,265	100.2792	99.3053	100.5938	101.3254	1.6151	96.2623	103.0603	-0.5393	2.7536
BCI	1,105,265	99.8937	99.3127	99.9651	100.6066	1.1112	95.5984	102.2237	-0.8234	4.6671

Table 4: Predicting Systemic Risk ($\Delta CoVaR$)

Notes: This table summarises the coefficient estimates of the linear panel data model, outlined in Equation 11. All variables are described in Table A1. The sample period runs from 1991 to 2020. The cross section comprises a total of 11,448 companies, with a varying number of companies in each year. The model is estimated by means of the random and fixed effects estimation methods. Robust standard errors are indicated in round parentheses. Asterisks **, * denote the 1% and 5% levels of significance, respectively.

	Systemic Risk ($\Delta CoVaR$)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OILRV	0.478**						
	(0.032)						
OILCV		1.878**					
		(0.034)					
OVX			10.953**				
			(0.067)				
SSV				-1.600**	-0.774**	-0.764**	-0.764**
				(0.021)	(0.024)	(0.024)	(0.024)
ADV				0.733**	1.437**	1.439**	1.439**
				(0.019)	(0.022)	(0.022)	(0.022)
IDV				-1.729**	-0.227**	-0.213**	-0.213**
				(0.023)	(0.027)	(0.027)	(0.027)
LNTA					0.015**	0.011**	0.011**
					(0.003)	(0.004)	(0.004)
LEV					-0.006**	-0.006**	-0.006**
					(0.001)	(0.001)	(0.001)
EPS					0.006**	0.002	0.002
					(0.002)	(0.002)	(0.002)
DVY					-0.019	-0.033	-0.033
					(0.017)	(0.018)	(0.018)
B/M					0.061**	0.073**	0.073**
					(0.005)	(0.005)	(0.005)
LIQ					0.021**	0.024**	0.024**
					(0.006)	(0.006)	(0.006)
LNVOLUME					-0.000	0.003	0.003
					(0.002)	(0.002)	(0.002)
TED					1.001**	0.998**	0.998**
					(0.016)	(0.016)	(0.016)
VIX					-2.380**	-2.388**	-2.388**
					(0.019)	(0.019)	(0.019)
CREDIT					2.908**	2.898**	2.898**
					(0.014)	(0.014)	(0.014)
CCI					-0.475**	-0.459**	-0.459**
					(0.052)	(0.052)	(0.052)
BCI					3.603**	3.568**	3.568**
					(0.041)	(0.041)	(0.041)
Cons	29.174**	29.064**	24.730**	30.377**	27.439**	27.467**	27.467**
	(0.096)	(0.096)	(0.026)	(0.097)	(0.131)	(0.128)	(0.128)
Firm FE	Y	Y	Y	Y	N	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	N	Y	N	N
$M \times Y \times I$ FE	N	N	N	N	N	N	Y
Obs	1,092,207	1,092,207	517,917	1,092,207	810,530	810,530	810,530
R^2	0.824	0.825	0.831	0.826	0.842	0.842	0.842

Table 5: Predicting Systemic Risk (MES)

Notes: This table summarises the coefficient estimates of the linear panel data model, outlined in Equation 11. All variables are described in Table A1. The sample period runs from 1991 to 2020. The cross section comprises a total of 11,448 companies, with a varying number of companies in each year. The model is estimated by means of the random and fixed effects estimation methods. Robust standard errors are indicated in round parentheses. Asterisks **, * denote the 1% and 5% levels of significance, respectively.

	Systemic Risk (MES)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OILRV	5.266**						
	(0.199)						
OILCV		6.957**					
		(0.207)					
OVX			22.020**				
			(0.324)				
SSV				0.741	-0.224*	-0.216*	-0.222*
				(0.723)	(0.126)	(0.126)	(0.126)
ADV				2.457**	2.744**	2.750**	2.728**
				(0.112)	(0.114)	(0.115)	(0.115)
IDV				-5.845**	-4.366**	-4.380**	-4.359**
				(0.137)	(0.142)	(0.143)	(0.143)
LNTA					-0.266**	-0.119**	-0.118**
					(0.013)	(0.021)	(0.021)
LEV					0.030**	0.032**	0.032**
					(0.004)	(0.004)	(0.004)
EPS					-0.168**	-0.137**	-0.137**
					(0.011)	(0.011)	(0.011)
DVY					0.033	0.177	0.183
					(0.085)	(0.096)	(0.096)
B/M					-0.377**	-0.397**	-0.396**
					(0.025)	(0.030)	(0.030)
LIQ					0.010	-0.040	-0.039
					(0.029)	(0.034)	(0.034)
LNVOLUME					0.246**	0.232**	0.231**
					(0.011)	(0.012)	(0.012)
TED					2.161*	2.177**	2.169**
					(0.083)	(0.084)	(0.084)
VIX					2.379**	2.380**	2.369**
					(0.098)	(0.099)	(0.099)
CREDIT					-1.696**	-1.700**	-1.689**
					(0.072)	(0.072)	(0.072)
CCI					5.180**	5.166**	5.108**
					(0.272)	(0.274)	(0.274)
BCI					-10.110**	-10.090**	-10.058**
					(0.220)	(0.221)	(0.221)
Cons	17.728**	17.585**	11.996**	19.067**	18.078**	17.443**	17.574**
	(0.556)	(0.556)	(0.121)	(0.562)	(0.675)	(0.676)	(0.676)
Firm FE	Y	Y	Y	Y	N	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	N	Y	N	N
$M \times Y \times I$ FE	N	N	N	N	N	N	Y
Obs	1,092,207	1,092,207	517,917	1,092,207	810,530	810,530	810,530
R^2	0.017	0.017	0.036	0.019	0.028	0.026	0.025

Table 6: Industry Estimation Results

Notes: This table summarises the coefficient estimates of the linear panel data model, outlined in Equation 11. All variables are described in Table A1. The sample period runs from 1991 to 2020. The cross section comprises a total of 11,448 companies, with a varying number of companies in each year. The model is estimated by means of the random and fixed effects estimation methods. Robust standard errors are indicated in round parentheses. Asterisks **, * denote the 1% and 5% levels of significance, respectively.

	EX-Energy Firms		Oil Users		Non-Oil Users	
	$\Delta CoVaR$	MES	$\Delta CoVaR$	MES	$\Delta CoVaR$	MES
	(1)	(2)	(3)	(4)	(5)	(6)
SSV	-0.781**	-0.188**	-0.810**	-0.086	-0.746**	-0.325**
	(0.021)	(0.054)	(0.027)	(0.068)	(0.032)	(0.087)
ADV	1.436**	1.360**	1.357**	1.411**	1.540**	1.337**
	(0.017)	(0.049)	(0.023)	(0.063)	(0.027)	(0.077)
IDV	-0.214**	-1.756**	-0.190**	-1.689**	-0.237**	-1.895**
	(0.023)	(0.043)	(0.030)	(0.058)	(0.036)	(0.064)
LNTA	0.011**	-0.046**	0.020**	-0.043**	0.001	-0.057**
	(0.004)	(0.007)	(0.006)	(0.010)	(0.006)	(0.010)
LEV	-0.006**	0.008**	-0.007**	0.008**	-0.006**	0.006*
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)
EPS	0.001	-0.053**	0.000	-0.058**	0.003	-0.045**
	(0.002)	(0.004)	(0.003)	(0.005)	(0.004)	(0.006)
DVY	-0.031*	0.045	-0.038	0.096**	-0.020	-0.041
	(0.015)	(0.026)	(0.020)	(0.032)	(0.022)	(0.040)
B/M	0.072**	-0.153**	0.071**	-0.151**	0.074**	-0.160**
	(0.007)	(0.011)	(0.009)	(0.017)	(0.009)	(0.015)
LIQ	0.023**	-0.017	0.019*	-0.041**	0.029*	-0.002
	(0.007)	(0.011)	(0.009)	(0.016)	(0.011)	(0.016)
LNVOLUME	0.002	0.088**	-0.007	0.097**	0.012*	0.083**
	(0.003)	(0.005)	(0.004)	(0.007)	(0.005)	(0.007)
TED	0.988**	0.753**	0.982**	0.879**	0.995**	0.642**
	(0.015)	(0.032)	(0.021)	(0.041)	(0.023)	(0.051)
VIX	-2.378**	1.105**	-2.303**	1.141**	-2.466**	1.098**
	(0.023)	(0.034)	(0.031)	(0.045)	(0.034)	(0.053)
CREDIT	2.875**	-0.765**	2.812**	-0.710**	2.922**	-0.859**
	(0.020)	(0.026)	(0.026)	(0.035)	(0.031)	(0.040)
CCI	-0.476**	2.170**	-0.457**	2.122**	-0.530**	2.272**
	(0.114)	(0.099)	(0.158)	(0.132)	(0.167)	(0.153)
BCI	3.537**	-4.288**	3.763**	-3.550**	3.238**	-5.299**
	(0.076)	(0.099)	(0.105)	(0.130)	(0.112)	(0.154)
Cons	27.510**	1.580**	27.406**	0.518	27.729**	3.007**
	(0.117)	(0.260)	(0.145)	(0.319)	(0.199)	(0.439)
Firm FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
$M \times Y \times I$ FE	Y	Y	Y	Y	Y	Y
Obs	754,749	754,247	414,328	414,028	331,748	331,598
R^2	0.842	0.025	0.842	0.025	0.841	0.027

Table 7: Predicting Unsystematic Risk

Notes: This table summarises the coefficient estimates of the linear panel data model, outlined in Equation 11. All variables are described in Table A1. The sample period runs from 1991 to 2020. The cross section comprises a total of 11,448 companies, with a varying number of companies in each year. The model is estimated by means of the random and fixed effects estimation methods. Robust standard errors are indicated in round parentheses. Asterisks **, * denote the 1% and 5% levels of significance, respectively.

	Unsystematic Risk (UNS)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OILRV	0.107						
	(0.061)						
OILCV		0.117					
		(0.063)					
OVX			0.566**				
			(0.091)				
SSV				-0.033	0.055	0.052	0.052
				(0.040)	(0.049)	(0.049)	(0.049)
ADV				0.059	0.071	0.064	0.064
				(0.036)	(0.044)	(0.044)	(0.044)
IDV				-0.313**	-0.264**	-0.269**	-0.269**
				(0.044)	(0.055)	(0.055)	(0.055)
LNTA					-0.746**	-0.703**	-0.703**
					(0.008)	(0.008)	(0.008)
LEV					0.131**	0.132**	0.132**
					(0.002)	(0.002)	(0.002)
EPS					-0.090**	-0.086**	-0.086**
					(0.004)	(0.004)	(0.004)
DVY					-0.097**	-0.065	-0.065
					(0.037)	(0.037)	(0.037)
B/M					0.341**	0.344**	0.344**
					(0.011)	(0.011)	(0.011)
LIQ					0.169**	0.174**	0.174**
					(0.013)	(0.013)	(0.013)
LNVOLUME					-0.274**	-0.279**	-0.279**
					(0.005)	(0.005)	(0.005)
TED					-0.036	-0.038	-0.038
					(0.032)	(0.032)	(0.032)
VIX					-0.028	-0.030	-0.030
					(0.038)	(0.038)	(0.038)
CREDIT					0.083**	0.085**	0.085**
					(0.028)	(0.028)	(0.028)
CCI					-0.376**	-0.384**	-0.385**
					(0.105)	(0.105)	(0.105)
BCI					0.002	0.015	0.015
					(0.084)	(0.084)	(0.084)
Cons	11.153**	11.151**	4.331**	11.275**	18.125**	16.465**	16.468**
	(0.161)	(0.161)	(0.035)	(0.164)	(0.327)	(0.242)	(0.242)
Firm FE	Y	Y	Y	Y	N	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	N	Y	N	N
$M \times Y \times I$ FE	N	N	N	N	N	N	Y
Obs	1,091,963	1,091,963	517,102	1,091,963	810,363	810,363	810,363
R^2	0.022	0.022	0.013	0.022	0.246	0.241	0.241

Table 8: Predicting Systematic Risk

Notes: This table summarises the coefficient estimates of the linear panel data model, outlined in Equation 11. All variables are described in Table A1. The sample period runs from 1991 to 2020. The cross section comprises a total of 11,448 companies, with a varying number of companies in each year. The model is estimated by means of the random and fixed effects estimation methods. Robust standard errors are indicated in round parentheses. Asterisks **, * denote the 1% and 5% levels of significance, respectively.

	Systematic Risk (BETA)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OILRV	0.220*						
	(0.097)						
OILCV		0.313**					
		(0.101)					
OVX			1.189**				
			(0.137)				
SSV				0.109	0.006	0.003	0.003
				(0.063)	(0.080)	(0.080)	(0.080)
ADV				0.065	0.199**	0.197**	0.197**
				(0.057)	(0.073)	(0.073)	(0.073)
IDV				-0.178*	0.016	0.008	0.008
				(0.070)	(0.090)	(0.090)	(0.090)
LNTA					0.850**	0.818**	0.818**
					(0.012)	(0.013)	(0.013)
LEV					-0.018**	-0.018**	-0.018**
					(0.003)	(0.003)	(0.003)
EPS					-0.117**	-0.115**	-0.115**
					(0.007)	(0.007)	(0.007)
DVY					-0.448**	-0.416**	-0.416**
					(0.060)	(0.061)	(0.061)
B/M					0.630**	0.622**	0.622**
					(0.018)	(0.018)	(0.018)
LIQ					0.076**	0.050*	0.050*
					(0.021)	(0.021)	(0.021)
LNVOLUME					0.645**	0.639**	0.639**
					(0.008)	(0.008)	(0.008)
TED					0.118*	0.115*	0.114*
					(0.053)	(0.053)	(0.053)
VIX					0.292**	0.293**	0.293**
					(0.063)	(0.063)	(0.063)
CREDIT					0.020	0.021	0.021
					(0.045)	(0.045)	(0.045)
CCI					-0.422*	-0.428*	-0.430*
					(0.172)	(0.172)	(0.172)
BCI					-0.650**	-0.644**	-0.643**
					(0.138)	(0.139)	(0.139)
Cons	59.863**	59.854**	55.496**	59.872**	51.376**	52.085**	52.088**
	(0.258)	(0.258)	(0.052)	(0.262)	(0.458)	(0.400)	(0.400)
Firm FE	Y	Y	Y	Y	N	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	N	Y	N	N
$M \times Y \times I$ FE	N	N	N	N	N	N	Y
Obs	1,088,249	1,088,249	516,655	1,088,249	806,580	806,580	806,580
R^2	0.011	0.011	0.003	0.011	0.156	0.154	0.153

Table 9: Predicting Total Risk

Notes: This table summarises the coefficient estimates of the linear panel data model, outlined in Equation 11. All variables are described in Table A1. The sample period runs from 1991 to 2020. The cross section comprises a total of 11,448 companies, with a varying number of companies in each year. The model is estimated by means of the random and fixed effects estimation methods. Robust standard errors are indicated in round parentheses. Asterisks **, * denote the 1% and 5% levels of significance, respectively.

	Total Risk (TR)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OILRV	0.375**						
	(0.056)						
OILCV		0.379**					
		(0.058)					
OVX			1.827**				
			(0.091)				
SSV				-0.140**	-0.095*	-0.096*	-0.096*
				(0.036)	(0.044)	(0.044)	(0.044)
ADV				0.093**	0.207**	0.205**	0.204**
				(0.033)	(0.040)	(0.040)	(0.040)
IDV				-0.248**	0.057	0.055	0.056
				(0.040)	(0.049)	(0.049)	(0.049)
LNTA					-1.147**	-1.099**	-1.099**
					(0.007)	(0.007)	(0.007)
LEV					0.164**	0.164**	0.164**
					(0.001)	(0.001)	(0.001)
EPS					-0.079**	-0.079**	-0.079**
					(0.004)	(0.004)	(0.004)
DVY					-0.047	-0.024	-0.024
					(0.033)	(0.033)	(0.033)
B/M					-0.170**	-0.164**	-0.164**
					(0.010)	(0.010)	(0.010)
LIQ					-0.189**	-0.179**	-0.179**
					(0.012)	(0.012)	(0.012)
LNVOLUME					-0.197**	-0.204**	-0.204**
					(0.004)	(0.004)	(0.004)
TED					-0.056	-0.055	-0.055
					(0.029)	(0.029)	(0.029)
VIX					0.020	0.021	0.021
					(0.034)	(0.034)	(0.034)
CREDIT					0.318**	0.318**	0.318**
					(0.025)	(0.025)	(0.025)
CCI					0.358**	0.365**	0.362**
					(0.094)	(0.094)	(0.094)
BCI					-0.153*	-0.149*	-0.148
					(0.075)	(0.075)	(0.075)
Cons	4.153**	4.149**	3.947**	4.306**	10.964**	9.976**	9.983**
	(0.147)	(0.147)	(0.035)	(0.149)	(0.277)	(0.217)	(0.217)
Firm FE	Y	Y	Y	Y	N	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	N	Y	N	N
$M \times Y \times I$ FE	N	N	N	N	N	N	Y
Obs	1,093,029	1,093,029	517,418	1,093,029	811,514	811,514	811,514
R^2	0.034	0.034	0.022	0.034	0.381	0.377	0.377

Table 10: Portfolio Analysis: Predicting $\Delta CoVaR$

Notes: This table summarises the coefficient estimates of the linear panel data model, outlined in Equation 11. In this table, we rank stocks into quantile portfolios of firm size, unsystematic, and systematic risk. All variables are described in Table A1. The sample period runs from 1991 to 2020. The cross section comprises a total of 11,448 companies, with a varying number of companies in each year. The model is estimated by means of the random and fixed effects estimation methods. Robust standard errors are indicated in round parentheses. Asterisks **, * denote the 1% and 5% levels of significance, respectively.

	Panel A: Ranking on Firm Size				
	1 LOW	2	3	4	5 HIGH
SSV	-0.690**	-1.165**	-0.829**	-0.404**	-0.448**
	(0.050)	(0.046)	(0.052)	(0.061)	(0.064)
ADV	1.429**	1.142**	1.411**	1.388**	1.684**
	(0.048)	(0.045)	(0.048)	(0.051)	(0.052)
IDV	-0.106	-0.148**	-0.205**	-0.186**	-0.216**
	(0.060)	(0.057)	(0.060)	(0.064)	(0.060)
Controls	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
$M \times Y \times I$ FE	Y	Y	Y	Y	Y
Obs	199,467	202,181	166,738	124,547	117,597
R^2	0.825	0.835	0.843	0.857	0.861
	Panel B: Ranking on Unsystematic Risk				
	1 LOW	2	3	4	5 HIGH
SSV	-0.897**	-0.060	-0.458**	-1.352**	-0.952**
	(0.061)	(0.050)	(0.048)	(0.048)	(0.054)
ADV	2.260**	1.222**	0.950**	1.009**	1.526**
	(0.049)	(0.041)	(0.044)	(0.049)	(0.054)
IDV	0.440**	0.978**	-0.027	-1.324**	-0.816**
	(0.053)	(0.049)	(0.056)	(0.064)	(0.068)
Controls	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
$M \times Y \times I$ FE	Y	Y	Y	Y	Y
Obs	87,800	153,608	181,488	192,386	193,514
R^2	0.805	0.828	0.847	0.851	0.820
	Panel C: Ranking on Systematic Risk				
	1 LOW	2	3	4	5 HIGH
SSV	-0.621**	-0.345**	-0.677**	-0.582**	-1.334**
	(0.059)	(0.058)	(0.052)	(0.051)	(0.049)
ADV	1.461**	1.218**	1.630**	1.517**	1.243**
	(0.055)	(0.051)	(0.047)	(0.045)	(0.048)
IDV	0.006	-0.545**	-0.476**	-0.245**	0.043
	(0.069)	(0.065)	(0.058)	(0.054)	(0.060)
Controls	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
$M \times Y \times I$ FE	Y	Y	Y	Y	Y
Obs	142,704	135,996	162,142	175,333	188,949
R^2	0.827	0.853	0.851	0.853	0.836

Figure 1: Evolution of Oil Volatility Shocks over the years

Notes: The Figure depicts the evolution of different oil volatility shock time series.

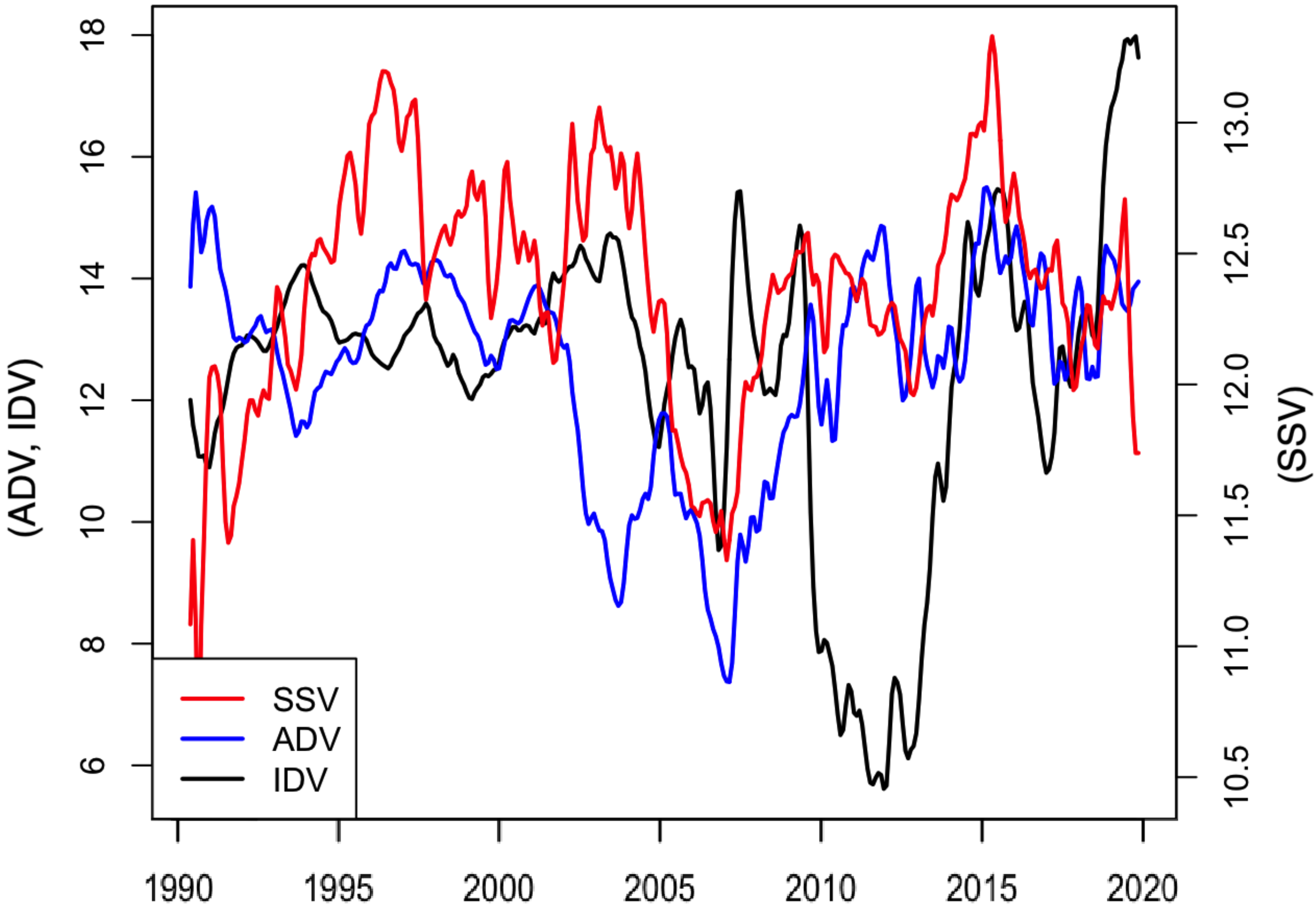


Figure 2: Evolution of Systemic Risk over the years

Notes: The Figure depicts the evolution of different time series. The time-series are calculated as the weighted average of all firms for any year given.

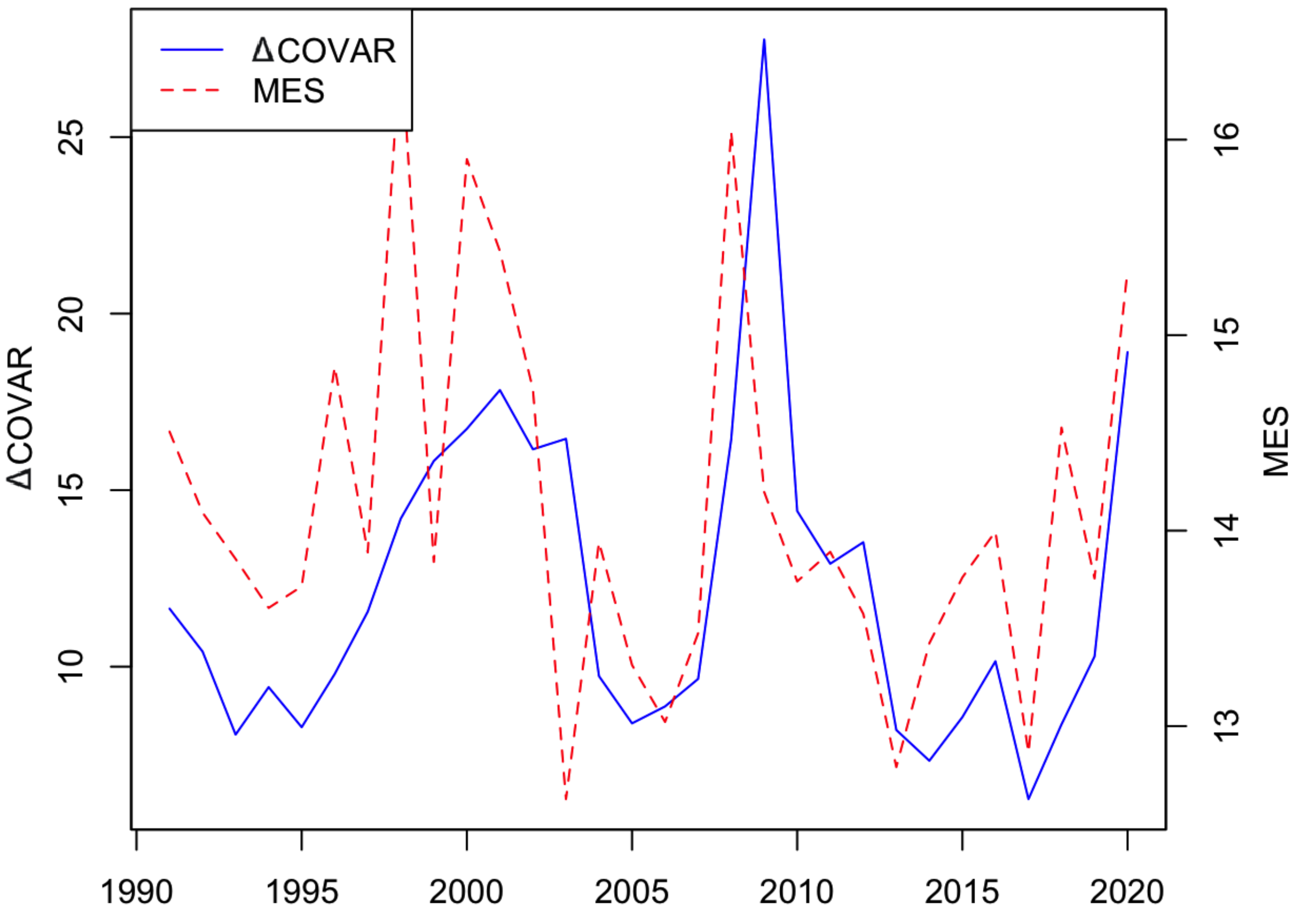
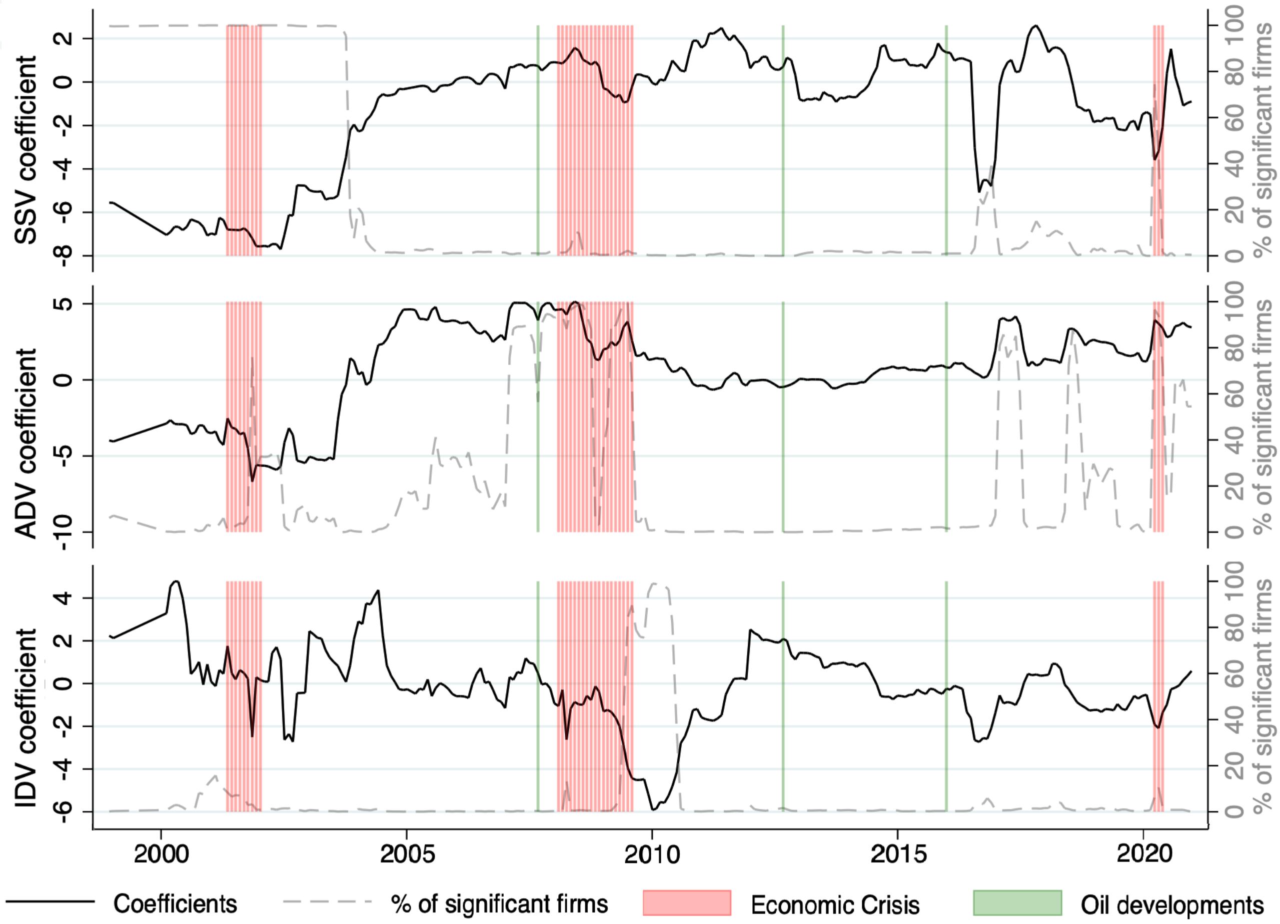


Figure 3: Time varying coefficients of Systemic risk ($\Delta CoVaR$)

Notes: The figure shows the time varying coefficients of the three oil volatility shocks on systemic risk based on a rolling window of 60 month-observations. The first 60 observations are also a burning period. It also depicts the the percentage of firms that are significantly affected by these oil shocks at 5% level.



Appendix

Table A1: Variables Definitions

Notes: This table describes the variables used in this study. Panel A shows the oil related variables. Panel B describes the stock market related variables. Finally, Panel C shows the ~~other~~ control variables. Column 1 shows the abbreviation of the variables. Column 2 describes the variables. Column 3 indicates the source of data for each variable.

Variables	Definitions	Source
	Panel A: Oil variables	
OILR	Oil price return from WTI spot prices. Calculated as $OILR = ln(OIL\ price_t) - ln(OIL\ price_{t-1})$	Energy information administration (https://www.eia.gov)
OILRV	The realized oil price volatility. It is computed as the square root of the sum of the daily squared oil price returns as shown in Equation 1	Authors' calculations
OILCV	The conditional oil price volatility. It is the conditional standard deviation of oil returns as shown in Equation 2	Authors' calculations
OVX	The implied oil price volatility	Bloomberg
SSV	The supply-side oil price volatility as shown in Equation 6	Authors' calculations
ADV	The aggregate demand oil price volatility as shown in Equation 6	Authors' calculations
IDV	Idiosyncratic oil price volatility as shown in Equation 6	Authors' calculations
	Panel B: Stock market variables	
$\Delta CoVaR$	Systemic risk. It is defined as the contribution of Value at Risk (VaR) of one firm to the Value at Risk of the industry. It is calculated as shown in Equation 9	Authors' calculations
MES	Marginal Expected Shortfall is defined as the short-run expected equity loss conditional on the market taking a loss greater than its Value-at-Risk at 5%. It is calculated as shown in Equation 10	Authors' calculations
UNS	Unsystematic risk. The average rolling window (251 days) standard deviation of the residuals from the five factor model for each month, as shown in Equation 14	Authors' calculations
BETA	Systematic risk. The average rolling window (251 days) beta of the five factor regression, as shown in Equations Equation 15	Authors' calculations
TR	Total risk. The average rolling window (251 days) standard deviation of $R_{i,s}$ for each month, as shown in Equation 16	Authors' calculations
	Panel C: Control variables	
LNTA	Natural logarithm of firm's total assets	Compustat
LEV	Leverage. Total debt / Total equity	Compustat
EPS	Earnings per share	Compustat
DVY	Dividend yield	Compustat
B/M	Book-to-market ratio	Compustat
LIQ	Liquidity ratio. Current assets / Current liabilities	Compustat
LNVOLUME	Natural logarithm of trading volume	Compustat
TED	TED is defined as the difference between the 3 month LIBOR rate and Treasury bill rate	FRED
VIX	VIX volatility index	FRED
CREDIT	Credit is the spread between Moody's Baa corporate bond and the 10-year treasury bond	FRED
CCI	Consumer confidence index. It is an indicator that provides an indication of future developments of households' consumption and saving, based upon answers regarding the market sentiment	OECD
BCI	Business confidence index. It is an indicator that provides information on future developments, based upon opinion surveys on developments in production, orders and stocks of finished goods	OECD

Figure A1: Times Series of Firm Risks

Notes: The Figure depicts the evolution of different time series. The time-series are calculated as the weighted average of all firms for any year given.