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Common Determinants of Credit Default Swap Premia in the North American Oil and Gas Industry. A Panel BMA Approach

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Abstract: This study discovered market determinants of credit default swap (CDS) spreads in the North American oil and gas industry. Due to the limited theoretical background on market sources of CDS price fluctuations, we chose to alleviate model uncertainty and possible misspecification issues using Bayesian model averaging. This robust framework allowed us to aggregate results from a vast number of linear panel models estimated over the 2017–2020 period. We identified oil price volatility, major shifts in the OPEC+ supply policy, natural gas prices and industrial metal prices as the most robust determinants of CDS spreads. We show that following the onset of the COVID-19 pandemic, oil prices ceased to be a notably important determinant of credit risk, as factors indirectly related to oil prices, such as global and sectoral uncertainty, financial conditions and the macroeconomic stance became more influential. Additionally, we show that the CDS spreads of shale companies are determined by similar common factors, but they are more sensitive to the OPEC+ decisions on the global supply and are less affected by the domestic activity. Finally, we also prove that our modelling approach may help investors and risk officers to identify robust determinants behind the dynamics of credit risk.

Keywords: credit risk; credit default swaps; Bayesian model averaging; robust determinants; COVID-19; oil and gas sector

JEL Classification: C33; C58; Q43

1. Introduction

The current pandemic crisis has vividly demonstrated the significant increase in the default risk of firms from the oil and gas industry in the US and Canada. Since the introduction of the combined technology of hydraulic fracturing and horizontal well drilling in 2011, the oil market has undergone revolutionary changes. This technological advancement has granted access to cheap, hydrocarbon-rich shale deposits in the US and Canada. Therefore, since its introduction, it has been hailed as the shale oil and gas revolution. On its account, the US has turned from a large net importer to a net exporter of crude oil in the following years, while Canada has become the fourth largest producer and the third largest exporter. However, the large-scale shale oil extraction in North America has propelled the OPEC cartel in 2014 to oversupply the market of crude oil, thereby provoking the oil prices to plummet. The premise for these actions was based upon the fact that for unconventional sources the break-even point is still higher than for largest conventional producers, such as Saudi Arabia. As a result, the shale oil and gas revolution has increased the dependency of oil and gas producers on global

factors, the price of oil in particular. Extreme variation in oil prices during the COVID-19 pandemic has confronted multiple agents—both suppliers and investors—with the fragility of the industry to such unprecedented shocks. Large swings in the credit risk standings observed in 2020 for oil and gas firms have also uncovered a niche in understanding their development on the market. Consequently, an important question arises: what are the factors which jointly and significantly drive credit risk in the North American oil and gas industry? We analyze this issue by considering a large set of potential factors commonly observed at the market level.

Valuable sources of information about the credit risk associated with a given enterprise are credit default swaps (henceforth CDS) issued against bond-related liabilities, which essentially transfer the credit risk to another party. A CDS is an agreement under which one of the transaction parties agrees to repay the debt due to the other party when a particular default event stated in the CDS contract occurs, in exchange for an agreed remuneration. In practice, this default event is a failure to pay the principal debt by the primary debtor, whereas the agreed remuneration is expressed as the CDS spread that denotes the cost of transferring the credit risk. If the probability of default increases, the spread of the CDS rises. In this paper, we use single-name CDS spreads as a measure of credit risk, as they react immediately to the information on the condition of underlying firms.

From the empirical perspective, a crucial problem is that specific guidelines regarding the sources of CDS spreads variability in the oil and gas industry are scarce. Seemingly, crude oil prices should be the most reliable determinant of CDS spreads as the profitability of firms in the oil and gas industry crucially depends on the price of its main output. However, given the fact that oil prices are perceived as a barometer for global demand, financial conditions, geopolitical tensions and are frequently used in investment strategies, e.g., [1–3], a variety of factors determine their level [4]. As a consequence, the relationship between oil prices and the spreads of CDS issued for bond-related liabilities of oil companies is a high-dimensional phenomenon. Therefore, given the proliferation of potential, common market determinants of CDS spreads, drawing inference from a single model would be unquestionably affected by specification uncertainty and potential misspecification. On the one hand, widely known techniques for dimensionality reduction, such as classical factor analysis, are not particularly suitable for statistical inference when dealing with non-normally distributed observations, as the financial market data [5]. On the other hand, other variable selection methods such as best subsets regression [6] and Bayesian SSVS explicitly ignore the model uncertainty issues (see [7] for a thorough discussion of challenges in the methods suitable for big data). Therefore, a common approach towards controlling for model uncertainty in such instances relies on various model averaging techniques.

In this context, Bayesian model averaging (henceforth BMA) provides a robust framework for inference. This approach essentially utilizes information from every possible empirical model that can be constructed from a predetermined set of explanatory variables. This information, stemming from the entire model space, is then averaged in a specific way using Bayesian inference in order to derive posterior probabilities for all regressors and all considered models. Consequently, as the information from the entire model space is incorporated into the results, this approach explicitly indicates robust regressors and addresses model uncertainty, while mitigating the risk of data-mining and inferring from a potentially misspecified model chosen subjectively by the researcher.

In this paper we use BMA techniques, which are tailored to deal with an extremely large set of possible model specifications. To the best of our knowledge, this is the first time this framework is applied to identify a set of robust determinants of fluctuations in single-name CDS spreads in the oil and gas industry in the US and Canada. Specifically, we consider factors that are related to different aspects of the economy, i.e., real, financial, monetary, uncertainty and administrative channels. We also investigate whether these determinants have markedly changed during the recent outbreak of the COVID-19 pandemic that resulted in a massive decline in demand for oil and a subsequent plummet in oil prices. Moreover, throughout our analysis we also zoom in on the determinants of CDS spreads for firms active in the shale sector, particularly heavily affected by the recent coronavirus crisis.

Previewing the results, we identify a diverse set of variables that determine the dynamics of CDS spreads in the oil and gas industry in the North America. We show that there exists a close, positive relationship between the forward looking market assessment of the risk of oil prices and the market view of the credit risk of oil and gas firms. This indicates that the uncertainty regarding the development in oil prices is a key factor affecting CDS spreads. We also report that radical changes in the OPEC supply policy impact CDS spreads to a major extent. In particular, the fiasco of the talks between OPEC and major non-OPEC producers and exporters has considerably increased the credit risk for the North American oil and gas firms, whereas unprecedented oil supply cuts have lowered the default risk, albeit to a much smaller extent. Moreover, we report that natural gas prices, recently decoupled from oil prices, also provide significant explanatory power for the fluctuations in the CDS spreads. Furthermore, industrial metal prices correlate negatively with the CDS spreads, which indicates the influence of the global economic stance on credit risk. Finally, we argue that both the overall financial conditions in the US and various channels related to the global and sectoral uncertainty or risk aversion affect the development in CDS spreads. Sensitivity analyses conducted in the paper point to the overall robustness of our results but reveal that prior to the outburst of the COVID-19 pandemic oil prices have been among the decisive determinants of CDS spreads. The interpretation of the results holds regardless of the analyzed sample of firms.

The rest of the paper is organized as follows. Section 2 reviews the literature. Section 3 focuses on the applied methodology. Section 4 presents the data used for this research. Section 5 provides the results for the baseline specification while Section 6 contains sensitivity analysis. In Section 7 we provide an additional set of results for the firms active in the shale oil and gas sector. The last section concludes.

2. Literature Review

The literature on credit risk modelling focuses on the estimation of two risk parameters: the probability of default (PD) and the loss given default (LGD). These two parameters are identified as the key risk factors of the internal rating based approach, central to the Basel II regulations and their subsequent updates. As the estimates of PD and LGD are based mostly on internal data, their calculations outside of financial institutions are rare. Instead, the economic and financial literature focuses heavily on market data, e.g., the quotations of credit derivatives and their spreads.

Credit derivative (mostly CDS) spreads are a popular measure of credit risk extensively investigated in the literature. For instance, Finnerty et al. [8] studied the relation between CDS spreads and credit ratings. They documented the ability of the CDS market to anticipate credit rating change announcements, especially for non-investment-grade securities. The efficiency of CDS market in processing credit-related information has been also analyzed by Hull et al. [9], who provided evidence that CDS spreads respond significantly prior to downgrades or negative watchlistings announcements by the major rating agencies. Moreover, Norden and Weber [10] documented that CDS spreads anticipate rating reviews and downgrades earlier than stock prices do.

The key drivers of the variability in CDS spreads (in general, not restricted to the oil and gas industry) were analyzed, i.e., by Ericsson et al. [11], Tang and Yan [12], Malhotra and Corelli [13] and Aman [14]. Using univariate and multivariate regressions, Ericsson et al. [11] conclude that market volatility, leverage and investor sentiment have a substantial explanatory power in describing the fluctuations in CDS spreads. In turn, Tang and Yan [12] showed that GDP growth rate and its volatility along with jump risk in the equity market affect the average credit spreads, with the investor sentiment and the implied volatility being the most important determinants at the market and firm level, respectively. Additionally, using a simple vector autoregression framework, Malhotra and Corelli [13] analyzed stock and oil returns to the sectoral CDS spread and found the bidirectional causality between these asset classes. Moreover, they quantified also the impact of the US energy CDS market on the European one during the GFC. Next to stock market conditions, Aman [14] indicates the

important role of the unobserved yield curve factors in explaining CDS price dynamics across many US industrial sectors.

In the oil and gas global market, CDS spreads are used in sovereign and corporate default risk analyses. They proxy credit risk for oil exporting countries, as evidenced by Bouri et al. [15], Pavlova et al. [16] and Naifar et al. [17]. In their study on the sovereign risk of BRICS countries, Bouri et al. [15] show a strong relationship between CDS spreads and oil price volatility. Moreover, they argue that the oil price volatility helps in predicting the sovereign risk at various quantiles and lags. In a similar vein, Pavlova et al. [16] confirmed that there exists a directional spillover from the oil price risk (measured by the OVX index) to the credit risk of oil exporting countries, while the political variables, aggregate demand and supply shocks are relatively less important. These findings were further confirmed by Naifar et al. [17] for oil exporting countries, especially those with significant sovereign wealth funds, such as Saudi Arabia, UAE and Norway.

The studies on the transmission of market and credit risk among four oil-related industries (automotive, chemicals, natural gas and utility) were initiated by Hammoudeh et al. [18]. The authors show that the CDS spread indices of these industries are responsive to the VIX, both in the short and in the long run, with none of them being sensitive to SMOVE (the swaption expected volatility proxy), which unilaterally assembles risk migration from the VIX. In a more recent study, Balcilar et al. [19] employed futures prices for WTI oil and seven different measures of markets and credit risk (CDS from four oil-related sectors, along with indices VIX, MOVE and SMOVE) and showed the destabilizing effects of the Lehman Brothers' bankruptcy on all oil-related sectors and the significant risk transmission effects of oil market-related shocks. A subsequent study by Balcilar et al. [20] confirmed that the oil market is a primary source of risk transmission for all the oil-related CDS.

Taking the aforementioned into account, to the best of our knowledge, there are limited theoretical frameworks underpinning the development in CDS spreads for the firms active in the oil and gas industry. Therefore, we decided to use BMA to uncover the determinants of this measure of credit risk. The BMA approach has already been applied for the identification of the driving forces of credit risk at the firm level by González-Aguado and Moral-Benito [21], but their analysis was limited to the choice of firm-specific variables in a probit model of corporate default. Hence, the authors did not explain the variability in CDS spreads. Commonly, BMA techniques are used in attempts to find robust determinants of economic growth. Throughout the last two decades a number of prominent papers have contributed to this strand of literature, simultaneously extending the application of the BMA from simple cross-sectional regression to static and dynamic, even potentially non-linear panel approaches, e.g., [22–29]. BMA is also quite extensively used for macroeconomic analyses and forecasts [30–33]. In turn, the application of BMA is far less frequent in the financial literature. Recently, this approach has been employed to assess the determinants of the sovereign credit risk and defaults [34,35], whereas Gernát et al. [36] disentangle the driving forces behind the stock price volatility in the U.S. financial sector. Finally, BMA can be also used for prediction or model selection due to the shrinkage it provides, as suggested by the encouraging results of an out-of-sample exchange rate forecasting exercise performed by Wright [37]. In turn, Koop and Korobilis [38] underlined the usefulness of BMA in finding a parsimonious representation of the panel VAR specifications, thereby dealing with the issue of the proliferation of parameters.

Our contribution to the literature on the credit risk of oil and gas industry is twofold. First, instead of working with the credit risk aggregates, we consider individual firms to enhance the understanding of the determinants of CDS spreads. Second, we employ the BMA approach, so far not used in this context in the literature, to allow a data-driven selection of key factors given limited theoretical guidelines. Additionally, we reiterate our analysis on the subset of firms involved in shale oil and gas exploration, which recently have arguably been the main contributors to the overall credit risk of the oil and gas industry in the North America.

3. Methodology

In order to motivate our choice of the dependent variable, we discuss here shortly the pricing methodology for CDS instruments and their relation to credit risk. Next, we outline the Bayesian model averaging framework.

3.1. CDS as a Credit Risk Measure

We start this section by briefly presenting the idea for pricing a CDS contract. According to the theoretical model of Hull and White [39], in equilibrium the expected present value of CDS premium payments to the seller should equal the present value of the expected pay-off from the CDS contract to the buyer. The pricing formula of Hull and White [39] relates the CDS price positively to the probability of default of the underlying company and negatively to the recovery rate and the accrued interest. Knowing that the variability of credit spread comes predominantly from changes in the probability of default, CDS spread is a good measure of credit risk.

In our research we use single-name CDS spreads as a proxy for the credit risk. Given the relatively good liquidity of the CDS market, spreads should adequately reflect the probability of default. We use 5-year CDS spreads in our research, as the most popular contracts for corporate credit risk have 5-year tenors.

3.2. Bayesian Model Averaging

The BMA framework is a convenient methodology that allows one to draw robust inference from large datasets while accounting for considerable model uncertainty. Therefore, it is commonly employed in the empirical strand of literature whenever the researcher faces the problem of substantial model uncertainty. This is particularly vivid in the discussion on the determinants of economic growth, as mentioned in Section 2, since from theoretical standpoint multiple growth theories are similarly plausible and not mutually exclusive, with the validity of one not implying the falseness of another. As BMA allows the researcher to account for numerous potential determinants affecting the studied variable (e.g., country's development), it deals appropriately with model uncertainty.

BMA can also be highly valued in an opposite situation, when there are limited theoretical foundations and the researcher tries to draw robust inference, based on the empirical investigation of the subject. This is close to our case since there are only few guidelines regarding the determinants of common fluctuations in CDS spreads in the oil and gas industry. This forces us to take an agnostic attitude and employ BMA to assess which regressors exert a robust impact on the dependent variable. To this end, BMA conveniently helps us to explore a vast space of possible models and to formulate conclusions based on a very specific average across the entire model space in a robust manner.

Let us start from a linear observed common factor model for N time series observed over T periods as follows:

$$y_{it} = X_t\beta + \alpha_i + u_{it}$$

where y_{it} is the dependent variable for individual i , $i = 1, \dots, N$ at time t , $t = 1, \dots, T$, X_t is a vector of K potential explanatory variables, β is the $K \times 1$ vector of parameters, α_i is the unobserved, time-invariant individual firm-specific effects, and u_{it} is an idiosyncratic error term. We apply the fixed-effect transformation (Frisch-Waugh-Lovell theorem) to eliminate α_i :

$$y_{it} - \bar{y}_i = (X_t - \bar{X})\beta + (\alpha_i - \bar{\alpha}_i) + (u_{it} - \bar{u}_i) \iff \tilde{y}_{it} = \tilde{X}_t\beta + \tilde{u}_{it}, \quad (1)$$

where $\bar{y}_i = T^{-1} \sum_{t=1}^T y_{it}$, $\bar{X} = T^{-1} \sum_{t=1}^T X_t$ and $\bar{u}_i = T^{-1} \sum_{t=1}^T u_{it}$. After rearranging equation (1) to the following vector form: $y = X\beta + u$, where y is $NT \times 1$, β is $K \times 1$, X is $NT \times K$ and u is $NT \times 1$, we arrive at the equation that can be estimated via ordinary least squares and is incorporated into the BMA framework in a straightforward manner. By using fixed effects we avoid distributional assumptions on the unobservable heterogeneity at the firm level. Moreover, we allow firm-specific

effects to be correlated with other explanatory variables and focus on individual variations of CDS spreads within firms.

Note that in our case the matrix $X = [x_1, x_2, \dots, x_K]$ contains many potential explanatory variables, some bearing similar information, so that including them all in the model might be inefficient or even infeasible given the limited sample span. In turn, given K potential predictors there are 2^K different subsets $X_j \in X$, which means that the inference based on one particular model may introduce considerable subjectivity and skew the interpretation due to highly probable misspecification issues. Although for small K one might estimate all models and perform some form of averaging across all specifications, once K becomes large the computation burden is prohibitively exhaustive. To put this into perspective, investigating the dataset of $K = 38$ potential determinants of CDS spreads in our baseline scenario yields in total 274 877 906 944 different specifications, as we allow for any combination of the variables belonging to the set X to appear in the model.

To tackle the problem of model uncertainty in an efficient way, we thus continue with the BMA framework. Using Bayesian terminology, the general idea behind BMA is to compute the posterior probability of model j , which we denote as $p(M_j|y, X)$, and interpret it as the probability (or the weight) of the model proportional to the prior model probability $p(M_j)$, and the marginal likelihood of the model, $p(y|M_j, X)$, i.e., the probability of the data given the model M_j . Thus, the posterior model probability can be represented as follows using Bayes' theorem:

$$P(M_j|y, X) = \frac{p(y|M_j, X)p(M_j)}{p(y|X)} = \frac{p(y|M_j, X)p(M_j)}{\sum_{i=1}^{2^K} p(y|M_i, X)p(M_i)} \quad (2)$$

An important choice in the BMA framework relates to the elicitation of the model prior $p(M_j)$, which reflects researcher's beliefs. When establishing the prior information we take into account several alternatives. Firstly, we consider the uniform information prior, with each model being equally plausible $p(M_j) \propto 1$ or equally $p(M_j) = 2^{-K}$ to reflect the lack of prior knowledge. Secondly, Sala-i-Martin et al. [23] specify a binomial model prior, where the researcher establishes the expected prior model size $\bar{m}$ which in turn defines the probability of the variable inclusion θ via the relation $\theta = \bar{m}K^{-1}$. In this setup the prior model probability is proportional to $p(M_j) \propto (\theta)^{k_j}(1 - \theta)^{K-k_j}$, where k_j is the number of regressors in the model M_j . With the prior model size of $K/2$ one obtains $\theta = 0.5$, thereby effectively employing the uniform model prior. This indicates that the researcher is equally uncertain about the importance of each variable. Therefore, with $\theta < 0.5$ ($\theta > 0.5$) the prior distribution is tilted towards smaller (larger) models. This results from the intuitive assumption that each variable is independently included in the model with the prior probability θ . Alternatively, instead of fixing the probability of including each variable we impose a hyperprior for θ and assume that $\theta \sim \text{Beta}(a, b)$, an approach that allows one to reduce the impact of essentially arbitrary prior assumptions on the posterior probabilities as argued by Ley and Steel [25]. Ley and Steel [25] propose to fix $a = 1$ and choose b equal to $(K - \bar{m})\bar{m}^{-1}$ so that one should only assign the prior mean model size through $\bar{m}$. Hence, the prior model probability is set as $p(M_j) \propto \Gamma(1 + k_j)\Gamma((K - \bar{m})\bar{m}^{-1} + K - k_j)$. In our setup, for the binomial model prior we fix $\theta = K/4$ to reflect a more stringent approach than in the case of the uniform information prior. In turn, for the beta-binomial prior we set it in such a way so that $\theta = K/2$.

The second decision related to the choice of prior assumptions regards the estimation process. For each model M_j we consider a normal error structure—i.e., $\tilde{u}_{it} \sim N(0, \sigma^2)$. We place a non-informative, improper prior on the constant and the error variance, thereby assuming their even distribution over their domain, $p(\alpha_j) \propto 1$ and $p(\sigma) \propto \sigma^{-1}$, respectively. Moreover, we follow the current well-established approach and use a specific prior structure called the Zellner's g prior for the regression coefficients. In this framework for β_j coefficients we use conservative prior mean of zero to reflect our agnosticism regarding the significance of regressors. As for the variance, we define it according to the Zellner's g :

$$\beta_j|g \sim N(0, \sigma^2(gX_j'X_j)^{-1})$$

Here the hyperparameter g reflects the degree of certainty with respect to the value of parameters β_j being 0. With $g \rightarrow 0$ the importance of the prior rises, since $E[\beta_j|y, X, g, M_j] = g(1+g)^{-1}\hat{\beta}_j$, where $\hat{\beta}_j$ is the standard OLS estimate for model j . Conversely, with $g \rightarrow \infty$ the prior becomes non-informative. In eliciting the prior information for g we choose between (i) the unit information prior with $g = N$, (ii) the so-called BRIC prior suggested by Fernández et al. [40] with $g = \max\{N, K^2\}$, which asymptotically behaves either like the Bayesian information criterion or the risk information criterion, (iii) the risk information criterion by Foster and George [41] with $g = K^2$ and iv) the prior that mimics the Hannan–Quinn criterion with $g = \log(N)^3$. We also consider the model-specific prior, namely, empirical Bayes local g -parameter as in George and Foster [42], Hansen and Yu [43] or Liang et al. [44], which value is established using information contained in the data via maximum likelihood methods. In this approach $g_j = \max(0, F_j - 1)$ where $F_j = R_j^2(N - 1 - k_j)(1 - R_j^2)^{-1}k_j^{-1}$ and R_j^2 is the OLS R-squared of model M_j .

Given several possible approaches towards the prior elicitation, in our baseline framework we assume that θ follows a Beta distribution, whereas g equals to $\max\{N, K^2\}$, in line with the BRIC prior. We conduct the estimation by exploring the vast space of possible models with the use of the birth/death Markov Chain Monte Carlo Model Composition (MC³) sampler introduced by Madigan et al. [45]. This sampler relies on the Metropolis-Hastings algorithm. Specifically, in every replication of the MC³ procedure a random walk step is used to construct an alternative model to the active one by subtracting or adding a regressor. The chain moves to the alternative model with the probability given by the Bayes factor and prior odds. After estimation, inference is based on the models visited by the Markov chain instead of the entire—potentially untrackable—model space. As the quality of the MC³ approximation depends on the number of draws and the initial conditions, we discard the first burn-in draws in the amount of 1×10^6 and we infer from the posterior distribution constructed based on 9×10^6 draws. This vast number of draws provides high convergence, as indicated by the correlation coefficient between the analytical and MCMC posterior model probabilities approaching 1. We perform all computations in R with the modified routines provided in the BMS package [46].

In presenting the results, we compute conditional moments of regression coefficients as weighted averages, conditional on the inclusion of the analyzed regressor. In the BMA approach a given regressor is robust if its posterior inclusion probability (PIP, denoting the updated prior probability of including a given regressor by taking the model to the data) is bigger than prior mean see cf. [21]. To facilitate the interpretation of the results, entries in Tables 5 and 6 with the PIP exceeding 0.5 are reported in bold. Furthermore, conforming to the scales proposed by Kass and Raftery [47] and Eicher et al. [26], we classify the evidence of robustness of determinants into four categories: weak (50–75% PIP), substantial (75–95%), strong (95–99%) and decisive (above 99%). A more relaxed statistic of the significance of each regressor is the transformed coefficient approach. Raftery [48] suggests that a variable is considered effective if the ratio of the posterior mean to posterior standard deviation (PM/PSD) exceeds one in absolute terms. In a more stringent approach, Masanjala and Papageorgiou [24] apply the threshold value of 1.3, thereby approximating a 90% confidence interval in frequentist approaches. Here, we highlight variables as effective whenever the PM/PSD ratio is larger than 2 in absolute terms, thereby following Sala-i-Martin et al. [23] and González-Aguado and Moral-Benito [21]. This choice allows us to approximate 95% Bayesian coverage region that excludes zero. Further excellent discussion on the Bayesian model averaging can be found in Raftery et al. [49] or Hoeting et al. [50], while the discussion of the MC³ algorithms is provided in Moral-Benito [27], Cuaresma et al. [28] or extensively explained by Koop [51].

4. Data

Sample information. To include as many firms as possible, our dataset starts on the 8 January 2017 and ends on the 2 August 2020. Due to the fact that the sample includes the COVID-19 pandemic period, we also carried out additional estimations in the period preceding the outbreak of the virus, with the sample ending on the 29 December 2019. Throughout the study we used weekly data.

The dependent variable. In the baseline model we define our dependent variable as the individual CDS spreads (as weekly logarithmic changes) with a 5-year tenor for the oil and gas sector firms located in the United States and Canada, as listed in the first row of Table 1. We refer to this group of firms as the baseline sample. In an additional analysis, described in Section 7, we also consider a subsample of single-name CDS spreads for firms from the shale industry (Table 1, second row). We select the firms at least partly involved in shale oil or gas exploration or production. For brevity, we will refer to this group as the shale sample. Summary statistics for the individual CDS spreads calculated over the full time span are reported in Table 2, and Figure 1 depicts the heterogeneity across time and firms for CDS spreads in both samples.

Table 1. List of firms entering the baseline and shale samples.

Sample Considered	Companies with 5Y CDS Spreads
Oil & gas industry in the US and Canada (baseline sample)	36 companies: Anadarko Petroleum Corp, Andeavor Corp, Apache Corp, Canadian Natural Resources Ltd., Chevron Corp, ConocoPhillips, Continental Resources Inc./OK, Devon Energy Corp, EOG Resources Inc., ETC Sunoco Holdings LLC, Enbridge Energy Partners LP, Enbridge Inc., Energy Transfer LP, Energy Transfer Operating LP, Enterprise Products Operating LLC, Exxon Mobil Corp, Hess Corp, Kinder Morgan Energy Partners LP, Kinder Morgan Inc., Magellan Midstream Partners LP, Marathon Oil Corp, MarkWest Energy Partners LP, Murphy Oil Corp, Newfield Exploration Co, Noble Energy Inc., ONEOK Inc., ONEOK Partners LP, Occidental Petroleum Corp, Ovintiv Canada ULC, Pioneer Natural Resources Co, Sabine Pass Liquefaction LLC, Spectra Energy Capital LLC, Targa Resources Partners LP, TransCanada PipeLines Ltd., Valero Energy Corp, Williams Cos Inc./The.
Shale industry in the US and Canada (shale sample)	21 companies: Anadarko Petroleum Corp, Andeavor Corp, Apache Corp, ConocoPhillips, Continental Resources Inc./OK, Devon Energy Corp, EOG Resources Inc., Enbridge Energy Partners LP, Enbridge Inc., Hess Corp, Marathon Oil Corp, Murphy Oil Corp, Newfield Exploration Co, Noble Energy Inc., ONEOK Inc., ONEOK Partners LP, Occidental Petroleum Corp, Ovintiv Canada ULC, Pioneer Natural Resources Co, Targa Resources Partners LP, Williams Cos Inc./The.

Note: The 1st row of the table presents the list of firms active in the oil and gas industry in the US and Canada for which CDS spreads with 5-year tenor are available throughout the whole sample period. In the 2nd row, shale firms active in the US and Canada are reported for which CDS spreads with 5-year tenor are available throughout the whole sample period.

Table 2. Descriptive statistics of the credit default swap (CDS) spreads.

	Mean	SD	Min.	Max.	Skew.	Kurt.	ADF
Anadarko Petroleum Corp	0.01	0.17	−1.07	1.19	1.34	26.26	−5.23
Andeavor Corp	0.00	0.11	−0.82	0.76	−0.39	29.07	−4.32
Apache Corp	0.00	0.14	−0.75	1.20	3.01	40.23	−5.57
Canadian Natural Resources Ltd.	0.00	0.12	−0.34	1.06	3.45	32.08	−4.81
Chevron Corp	0.01	0.10	−0.18	0.76	4.25	31.74	−4.63
ConocoPhillips	0.00	0.18	−1.49	1.37	−0.72	48.07	−6.52
Continental Resources Inc./OK	0.00	0.09	−0.32	0.76	3.80	34.90	−5.06
Devon Energy Corp	0.00	0.13	−0.52	1.04	2.73	25.52	−5.71
EOG Resources Inc.	0.01	0.09	−0.18	0.76	4.26	33.27	−4.63
ETC Sunoco Holdings LLC	0.01	0.07	−0.18	0.76	5.96	61.30	−4.70
Enbridge Energy Partners LP	0.00	0.02	−0.18	0.18	0.29	38.82	−8.15
Enbridge Inc.	0.00	0.10	−0.36	0.82	2.84	25.24	−4.88
Energy Transfer LP	0.00	0.09	−0.45	0.76	2.69	34.93	−5.24
Energy Transfer Operating LP	0.00	0.13	−0.69	0.79	0.10	17.21	−6.42
Enterprise Products Operating LLC	−0.01	0.04	−0.37	0.32	−1.37	42.29	−6.90
Exxon Mobil Corp	0.01	0.18	−1.16	1.36	1.08	33.78	−6.73
Hess Corp	0.00	0.13	−0.44	1.05	3.00	29.13	−4.78
Kinder Morgan Energy Partners LP	0.00	0.10	−0.47	0.73	1.68	20.15	−5.79
Kinder Morgan Inc.	0.00	0.12	−0.70	0.97	1.93	35.47	−5.25
Magellan Midstream Partners LP	0.01	0.09	−0.18	0.76	4.20	33.17	−4.58
Marathon Oil Corp	0.00	0.11	−0.42	0.98	3.96	35.67	−6.29
MarkWest Energy Partners LP	0.00	0.10	−0.81	0.76	−0.55	48.12	−5.53
Murphy Oil Corp	0.00	0.14	−1.06	1.12	0.72	39.38	−4.99

Table 2. Cont.

	Mean	SD	Min.	Max.	Skew.	Kurt.	ADF
Newfield Exploration Co	0.00	0.09	−0.55	0.76	2.12	32.09	−5.55
Noble Energy Inc.	0.00	0.09	−0.33	0.76	3.33	32.80	−5.48
ONEOK Inc.	0.00	0.15	−0.69	0.89	0.53	16.22	−5.68
ONEOK Partners LP	0.00	0.13	−0.75	1.04	3.96	46.95	−5.82
Occidental Petroleum Corp	0.01	0.15	−0.25	1.75	8.62	96.17	−5.49
Ovintiv Canada ULC	0.00	0.09	−0.29	0.57	1.47	10.55	−4.91
Pioneer Natural Resources Co	0.00	0.08	−0.16	0.76	5.09	48.41	−5.60
Sabine Pass Liquefaction LLC	−0.01	0.11	−0.89	0.76	−1.31	36.44	−5.51
Spectra Energy Capital LLC	0.00	0.03	−0.22	0.23	−0.24	28.22	−4.81
Targa Resources Partners LP	0.00	0.09	−0.71	0.76	0.64	44.73	−5.53
TransCanada PipeLines Ltd.	0.00	0.06	−0.56	0.45	−1.60	47.65	−5.43
Valero Energy Corp	0.00	0.16	−0.89	0.82	0.54	12.79	−6.30
Williams Cos Inc./The	0.00	0.13	−0.82	0.94	1.04	27.36	−6.41

Note: Table 2 reports the descriptive statistics of the transformed dependent variable across all firms entering the baseline sample. In the table SD denotes standard deviation, Min. and Max. correspond to the minimum and maximum values, Skew. reports the skewness measure and Kurt. denotes the kurtosis. The last column reports the ADF statistics which indicate that all variables are in their stationary representations.

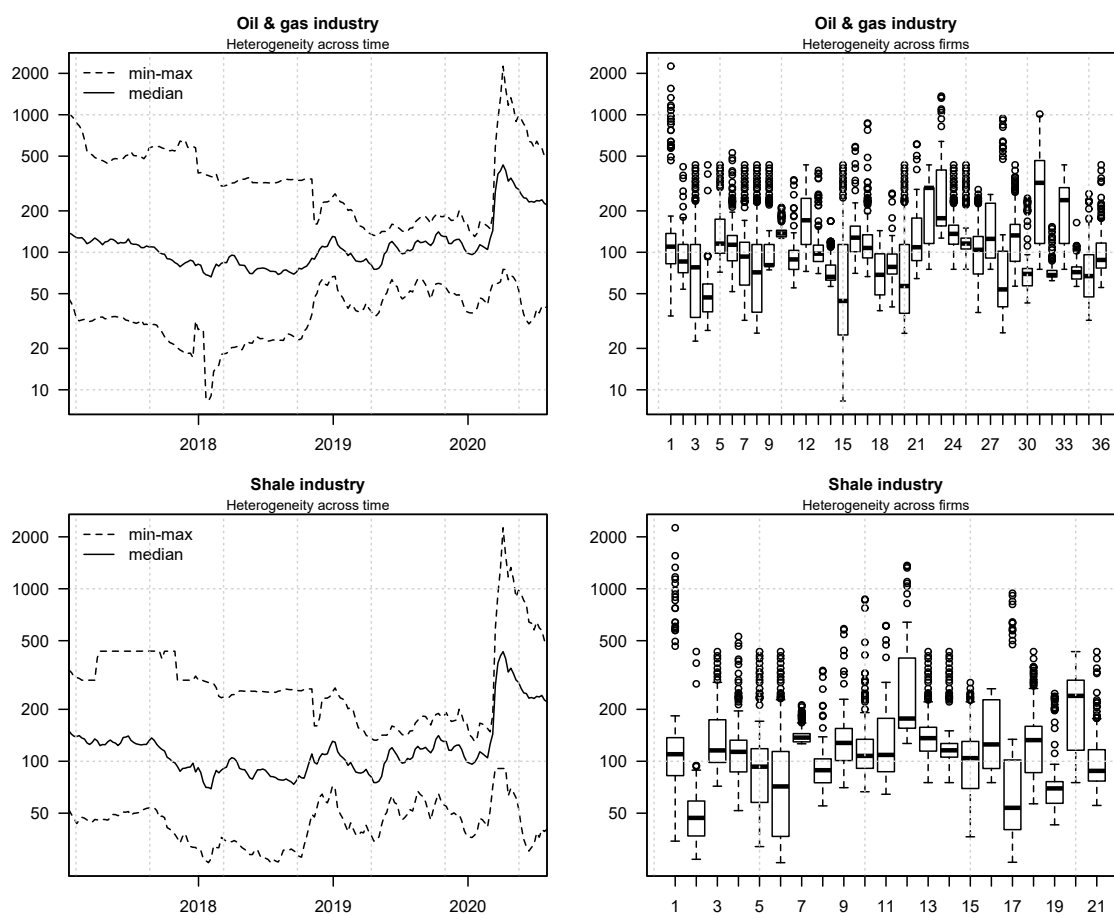


Figure 1. The development in CDS spreads. Note: The upper panels report the heterogeneity in spreads in the oil and gas industry in the US and Canada across time and across firms. The lower panels depict the development in spreads in a similar manner for the firms active in the shale industry in the US and Canada. For the right panel, the orders of firms in the top and bottom plots correspond to the orders of firms listed in Table 1 in rows 1 and 2, respectively. In all figures the vertical axes are on a logarithmic scale due to the large variability in the CDS spreads.

The explanatory variables. We consider in total $K = 38$ potential determinants and group them into several broad categories, indicated by a specific prefix. Table 3 reports all variables used in the paper along with their descriptions, categories, transformations to stationary representations and sources, while Figure 2 presents their fluctuation during the sample period considered. Table 4 summarizes the descriptive statistics for the explanatory variables of weekly frequency for the same period. In what follows, we briefly describe the broad categories and independent variables that enter the set of potential determinants.

Oil market fundamentals (OIL). Firstly, we account for several variables describing the situation in the oil market. Hence, we employ oil prices (futures WTI price in USD per barrel), the spread between the WTI and the Brent price of oil, total oil production and inventories (data reported by the US Department of Energy). We also consider the number of active oil rotary rigs to account for the changing capacity utilization in the oil sector. These data are drawn from Bloomberg.

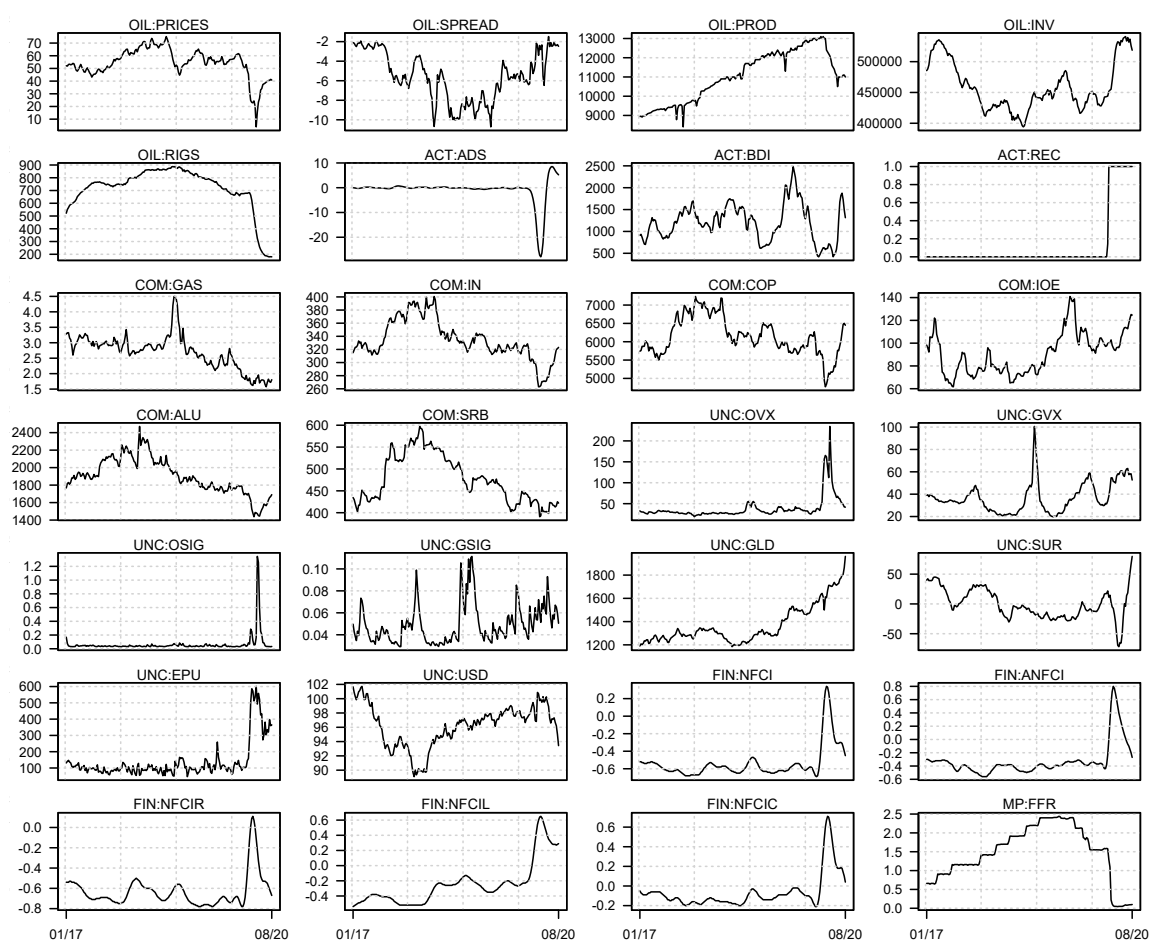


Figure 2. The development in the exogenous variables. Note: The figure shows the development in pre-transformed exogenous variables. For variables' definitions, transformations, categorization and sources the reader is referred to Table 3.

Table 3. Variables' labels, descriptions, categories, sources and transformations.

Variable	Description	Category	Transformation	Source
CDS5Y	Credit Default Swap (5Y Tenor)	CDS	$\Delta \ln$	Bloomberg
OIL:PRICES	Crude Oil Futures Prices (New York Mercantile Exchange)	Oil market fundamentals	$\Delta \ln$	Bloomberg
OIL:SPREAD	Spread between the WTI price and the Brent Price	Oil market fundamentals	Δ	Bloomberg
OIL:PROD	US DOE Crude Oil Total Production	Oil market fundamentals	$\Delta \ln$	Bloomberg
OIL:INV	US DOE Crude Oil Inventory Data (excluding Strategic Petroleum Reserve)	Oil market fundamentals	$\Delta \ln$	Bloomberg
OIL:RIGS	US Active Oil Rotary Rigs	Oil market fundamentals	$\Delta \ln$	Bloomberg
ACT:ADS	ADS US Business Conditions Index	Real activity	0–1	Aruoba et al. [52]
ACT:BDI	Baltic Exchange Dry Index	Real activity	$\Delta \ln$	Bloomberg
ACT:REC	Recession Indicator for the US (NBER dates)	Real activity	0–1	FRED
COM:GAS	Natural Gas Futures Prices (New York Mercantile Exchange)	Commodity prices	$\Delta \ln$	Bloomberg
COM:IN	S&P GSCI Industrial Metals Index	Commodity prices	$\Delta \ln$	Bloomberg
COM:COP	Copper Futures Prices (Chicago Mercantile Exchange)	Commodity prices	$\Delta \ln$	Bloomberg
COM:IOE	Iron Ore Futures Prices (Dalian Commodity Exchange)	Commodity prices	$\Delta \ln$	Bloomberg
COM:ALU	Aluminium Futures Prices (London Metals Exchange)	Commodity prices	$\Delta \ln$	Bloomberg
COM:SRB	Steel Rebar Futures Prices (London Metals Exchange)	Commodity prices	$\Delta \ln$	Bloomberg
UNC:OVX	Oil Prices Implied Volatility (CBOE Estimates Based on Option Prices)	Uncertainty	$\Delta \ln$	Bloomberg
UNC:GVX	Natural Gas Prices Implied Volatility (Bloomberg estimates)	Uncertainty	$\Delta \ln$	Bloomberg
UNC:OSIG	Oil Prices Historical Volatility (GARCH estimates)	Uncertainty	$\Delta \ln$	Own
UNC:GSIG	Natural Gas Prices Historical Volatility (GARCH estimates)	Uncertainty	$\Delta \ln$	Own
UNC:GLD	Gold Spot Prices	Uncertainty	$\Delta \ln$	Bloomberg
UNC:SUR	Citi Economic Surprise Index for Global Economy	Uncertainty	Δ	Bloomberg
UNC:EPU	US Economic Policy Uncertainty Index by Baker et al. [58]	Uncertainty	$\Delta \ln$	Bloomberg
UNC:USD	US Dollar Index	Uncertainty	$\Delta \ln$	Bloomberg
FIN:NFCI	National Financial Conditions Index	Financial conditions	Δ	FRED
FIN:ANFCI	Adjusted National Financial Conditions Index	Financial conditions	Δ	FRED
FIN:NFCIR	National Financial Conditions Index—Risk Subindex	Financial conditions	Δ	FRED
FIN:NFCIL	National Financial Conditions Index—Leverage Subindex	Financial conditions	Δ	FRED
FIN:NFCIC	National Financial Conditions Index—Credit Subindex	Financial conditions	Δ	FRED
MP:FFR	US Federal Funds Effective Rate	Monetary policy	Δ	Bloomberg
OE:250517	Extending the adjustment period (25 May 2017, 172nd OPEC meeting)	OPEC decisions	0–1	OPEC
OE:301117	Extending the adjustment period (30 November 2017, 173rd OPEC meeting)	OPEC decisions	0–1	OPEC
OE:220618	End of the pact (22 June 2018, 174th OPEC meeting)	OPEC decisions	0–1	OPEC
OC:061218	New supply cut (6 December 2018, 175th OPEC meeting)	OPEC decisions	0–1	OPEC
OE:010719	Extending the adjustment period (1 July 2019, 176th OPEC meeting)	OPEC decisions	0–1	OPEC
OC:051219	New supply cut (5 December 2019, 177th OPEC meeting)	OPEC decisions	0–1	OPEC
OF:050320	End of the pact (5 March 2020, 178th OPEC meeting)	OPEC decisions	0–1	OPEC
OC:090420	New supply cut (9 April 2020, 179th OPEC meeting)	OPEC decisions	0–1	OPEC
OE:060620	Extending the adjustment period (6th of June, 2020, 180th OPEC meeting)	OPEC decisions	0–1	OPEC
OE:150720	Easing of the production cuts (15 July 2020, OPEC+ decision)	OPEC decisions	0–1	OPEC

Note: The table presents the full list of variables used in the paper, along with their descriptions, categorizations, transformations and sources. $\Delta \ln$ denotes logarithmic differences; Δ denotes simple differencing; and 0–1 denotes that the variable is either binary or has been transformed to a binary representation.

Table 4. Descriptive statistics of exogenous variables.

	Mean	SD	Min.	Max.	Skew.	Kurt.	ADF
OIL:PRICES	0.00	0.17	−1.63	1.39	−1.86	73.40	−5.46
OIL:SPREAD	0.00	0.73	−3.19	3.27	0.52	7.00	−6.74
OIL:PROD	0.00	0.02	−0.12	0.12	−0.21	21.38	−5.06
OIL:INV	0.00	0.01	−0.03	0.04	0.14	2.96	−4.27
OIL:RIGS	−0.01	0.03	−0.15	0.05	−3.06	13.89	−4.78
ACT:ADS	0.37	0.48	0.00	1.00	0.56	1.31	N/A
ACT:BDI	0.00	0.10	−0.30	0.48	0.45	5.42	−5.53
ACT:REC	0.12	0.32	0.00	1.00	2.36	6.58	N/A
COM:GAS	0.00	0.05	−0.16	0.16	−0.08	4.37	−6.63
COM:IN	0.00	0.02	−0.07	0.04	−0.41	3.88	−5.43
COM:COP	0.00	0.02	−0.10	0.05	−0.82	6.41	−5.17
COM:IOE	0.00	0.05	−0.16	0.14	−0.73	5.24	−5.75
COM:ALU	0.00	0.02	−0.09	0.13	0.87	8.71	−6.06
COM:SRB	0.00	0.02	−0.07	0.10	0.72	7.96	−5.57
UNC:OVX	0.00	0.12	−0.43	0.74	2.22	16.61	−4.13
UNC:GVX	0.00	0.08	−0.30	0.44	0.64	10.37	−4.28
UNC:OSIG	−0.01	0.35	−0.84	2.10	1.54	11.04	−6.34
UNC:GSIG	0.00	0.17	−0.22	0.74	1.78	6.63	−6.69
UNC:GLD	0.00	0.01	−0.07	0.07	0.11	8.72	−4.83
UNC:SUR	0.26	5.90	−20.72	28.98	0.86	7.87	−3.94
UNC:EPU	0.00	0.27	−0.85	1.04	0.39	4.63	−6.36
UNC:USD	0.00	0.01	−0.02	0.04	0.89	9.16	−4.73
FIN:NFCI	0.00	0.04	−0.12	0.19	2.14	15.83	−3.97
FIN:NFCI	0.00	0.04	−0.10	0.28	3.52	22.50	−3.74
FIN:NFCIR	0.00	0.03	−0.11	0.16	1.62	13.51	−3.82
FIN:NFCIL	0.00	0.02	−0.05	0.12	2.26	11.89	−5.41
FIN:NFCIC	0.00	0.03	−0.09	0.14	1.87	13.07	−4.46
MP:FFR	0.00	0.08	−0.87	0.16	−6.51	67.65	−5.41

Note: The table reports the descriptive statistics of the exogenous variables after their transformations. In the table, SD denotes standard deviation, Min. and Max. correspond to the minimum and maximum values, Skew. reports the skewness measure and Kurt. denotes the kurtosis. The last column reports the ADF statistics which indicate that all variables are in their stationary representations (for binary variables this statistic is omitted). For variables' definitions, transformations, categorization and sources, the reader is referred to Table 3.

Economic activity (ACT). To measure economic activity in high frequency we rely on three measures. Firstly, we consider the Business Conditions Index developed by Aruoba et al. [52] for the US economy. However, given extreme swings of this measure following the COVID-19 pandemic we transform this proxy into a binary variable, assigning 1 (0) for each period when the original index indicates economic expansion (recession). As a second proxy of economic activity, we make use of the Baltic Exchange Dry Index that measures the prices of freights. This corresponds somewhat to the monthly proxy developed by Kilian [53]. Finally, we employ a traditional binary variable denoting the recession periods in the US economy which is provided by NBER. These data are sourced from Aruoba et al. [52], Bloomberg and FRED, respectively.

Commodity prices (COM). First, to account for the recent decoupling between the US oil and the US natural gas prices [54–56], we include the futures prices of the latter. Second, given the recent debate in the empirical literature on the usefulness of certain commodity prices in approximating business cycles [57], we include in our database five specific variables. We employ the S&P GSCI Industrial Metals Index which approximates the development in prices of most significant industrial metals. Additionally, we include the quotations for four industrial metals of great importance for the industrial production, namely, copper, iron ore, aluminium and steel rebar. The data on commodity prices are drawn from Bloomberg.

Uncertainty (UNC). This group is constituted of several variables proxying different sources of uncertainty that may impact the credit risk in the studied industry. We begin by considering two different volatility measures: the implied volatility of oil and natural gas prices calculated from

option prices by CBOE (sourced from Bloomberg) and the historical volatility of oil and natural gas prices approximated by the conditional sigma from the GARCH(1,1) model with skewed Student *t* distribution (own calculations based on the historical oil prices quotations). Moreover, we include in this category spot gold prices to account for periods of high risk aversion. We also make use of the Citi Economic Surprise Index which indicates whether macroeconomic readings positively (negatively) surprise professional forecasters, rendering this measure positive (negative). Next, we employ the US economic policy uncertainty index developed by Baker et al. [58] to account for the uncertainty related to the administrative decisions. Finally, we include the US dollar index as a broad measure of market sentiment given the role the US dollar plays in the international trade. With the exceptions of the oil and natural gas prices historical volatilities, the remaining variables in this group are sourced from Bloomberg.

Financial conditions (FIN). This block comprises of financial variables summarizing the overall and specific financial conditions in the US. To this end, we employ the National Financial Conditions Index developed by Brave and Butters [59] in its standard and adjusted form, and the three main subcomponents which are related to the level of risk, leverage and credit availability in the financial markets. These data are downloaded from FRED.

Monetary policy (MP). We use the US federal funds effective rate as an indicator of the monetary policy stance in the US, as disseminated by Bloomberg.

OPEC decisions (OI,OC,OE,OF). Finally, we consider several binary variables which indicate specific decisions undertaken throughout our sample period by the OPEC members and non-OPEC countries associated with OPEC. Specifically, we include three binary variables denoting production cuts (OC, on the 6 December 2018, 5 December 2019 and an unprecedented cut agreed on by the OPEC+ informal group on the 9 April 2020), five variables denoting the extension of the production cuts already in place (OE, on the 25 May 2017, on the 30 November 2017, on the 1 July 2019, on the 6 June 2020 and on the 15 July 2020), one variable denoting oil production increase (OI, on the 22 June 2018) and one variable denoting the fiasco of the talks held between OPEC members and major non-OPEC producers to cut oil production following the unprecedented decline in the demand for this commodity (OF, on the 5 March 2020). The decisions undertaken by OPEC during its meeting were accepted with a one day delay by non-OPEC members joining OPEC in efforts to stabilize global oil prices by curbing supply.

5. Baseline Results

In this section, we show results obtained for the baseline sample and the full time span. The BMA estimates are presented in the left part of Table 5, whereas Figure 3 shows the specifications of the models with the highest posterior model probability (PMP) that account in total for 95% of the PMP. Table 5 reports the posterior inclusion probability (PIP) of each independent variable which indicates the relevance and robustness of each regressor in explaining the variation in the dependent variable. Next, it shows the posterior mean (PM) together with the 95% quasi confidence bands (in square brackets), the posterior standard deviation (PSD) of the distribution for each parameter and the conditional positive sign (CPS) statistic which denotes how frequently the estimate is positive, conditional upon the inclusion of the regressor.

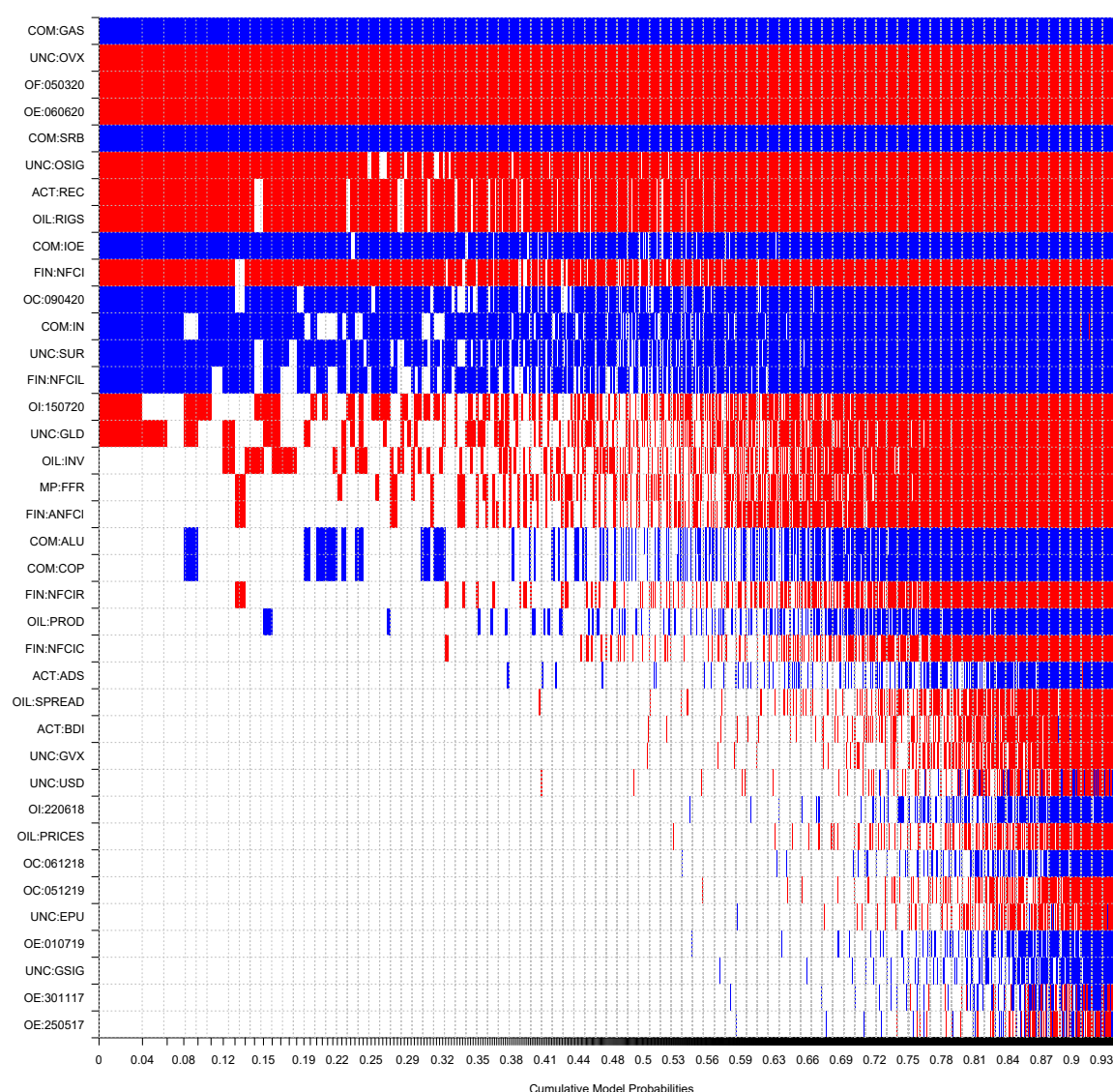


Figure 3. Model inclusion based on the models accounting for 95% of the posterior model probability (PMP). Note: Figure 3 illustrates a comprehensive overview of the models accounting for 95% of the PMP. The horizontal axis shows the best models according to their posterior model probabilities. The vertical axis illustrates the inclusion of subsequent variables in respective models. Red (blue) indicates that a particular variable enters the specification with a positive (negative) coefficient, whereas a white box indicates that a particular variable is not included in a specific model. For variables' definitions, transformations, categorization and sources, the reader is referred to Table 3.

In general, Table 5 shows that in the longer sample, a diverse set of variables determines the dynamics of CDS spreads. BMA identifies five regressors with decisive evidence of robustness (all of them highly effective) which come from various categories and enter every specification. The most evident are the natural gas prices and the implied volatility of oil prices. Negative and robust PM estimates at natural gas prices signify their important role for the profitability of firms and their credit risk in this industry. The results also show that natural gas prices have indeed decoupled from oil prices as their information contents significantly differ. For the latter, we show a positive relationship between the market assessment of the credit risk and the forward looking measure of market risk of oil price implied from options. This indicates that over the full sample the volatility in oil prices and not their level is crucial for CDS spreads. The next two variables with decisive evidence of robustness

are dummies corresponding to the recent turning point in the OPEC+ policy. These results show a considerable impact of crucial announcements made by OPEC and cooperating oil producing countries. In particular, following the fiasco of attempts to cut oil production, the credit risk for oil and gas companies increased significantly. Moreover, only extending the supply limits in June 2020 again negatively affected the default risk of the companies, thereby increasing the CDS spreads, albeit to a three-fold smaller extent. We also observe that changes in steel rebar futures prices correlate negatively with the credit risk. Since industrial metal prices are a barometer for the global demand, their fall tend to reflect weaker global demand (for oil as well) and thus lead to the increase in the default risk.

Table 5. BMA estimates for the baseline sample.

Variable	Estimates on 8 January 2017–2 August 2020					Estimates on 8 January 2017–29 December 2019				
	PIP	PM	PM Conf. bd.	PSD	CPS	PIP	PM	PM Conf. bd.	PSD	CPS
COM:GAS	1.000	−0.164 *	[−0.219, −0.109]	0.028	0.000	1.000	−0.139 *	[−0.192, −0.088]	0.027	0.000
UNC:OVX	1.000	0.129 *	[0.103, 0.156]	0.014	1.000	0.956	0.075 *	[0.039, 0.110]	0.018	1.000
OF:050320	1.000	0.370 *	[0.318, 0.417]	0.025	1.000			N/A		
OE:060620	1.000	0.123 *	[0.079, 0.166]	0.022	1.000			N/A		
COM:SRB	1.000	−0.375 *	[−0.507, −0.242]	0.068	0.000	0.264	−0.156 *	[−0.267, −0.044]	0.057	0.000
UNC:OSIG	0.906	0.016 *	[0.008, 0.025]	0.004	1.000	0.537	0.014 *	[0.005, 0.023]	0.004	1.000
ACT:REC	0.903	0.034 *	[0.018, 0.049]	0.008	1.000			N/A		
OIL:RIGS	0.900	0.363 *	[0.198, 0.528]	0.085	1.000	0.013	−0.083	[−0.294, 0.129]	0.108	0.050
COM:IOE	0.891	−0.106 *	[−0.162, −0.050]	0.029	0.000	0.372	−0.069 *	[−0.115, −0.023]	0.024	0.000
FIN:NFCI	0.809	0.585 *	[0.292, 0.800]	0.130	1.000	0.938	0.898 *	[0.424, 1.210]	0.190	1.000
OC:090420	0.804	−0.071 *	[−0.110, −0.032]	0.020	0.000			N/A		
UNC:SUR	0.772	−0.001 *	[−0.002, 0.000]	0.000	0.000	1.000	−0.002 *	[−0.002, −0.001]	0.000	0.000
COM:IN	0.761	−0.588 *	[−0.768, −0.403]	0.105	0.003	0.816	−0.351 *	[−0.586, −0.181]	0.101	0.000
FIN:NFCIL	0.658	−0.333 *	[−0.528, −0.137]	0.100	0.000	0.380	−0.348 *	[−0.577, −0.117]	0.118	0.000
OI:150720	0.445	0.057 *	[0.020, 0.095]	0.019	1.000			N/A		
UNC:GLD	0.363	0.284 *	[0.093, 0.477]	0.098	1.000	0.993	0.578 *	[0.303, 0.831]	0.134	1.000
OIL:INV	0.314	0.329 *	[0.099, 0.558]	0.117	1.000	0.165	0.256 *	[0.055, 0.459]	0.103	1.000
MP:FFR	0.267	0.065 *	[0.017, 0.112]	0.024	1.000	0.010	−0.011	[−0.056, 0.034]	0.023	0.070
FIN:ANFCI	0.259	0.275 *	[0.066, 0.505]	0.112	1.000	0.023	0.149	[−0.063, 0.360]	0.108	1.000
COM:ALU	0.250	−0.252 *	[−0.394, −0.089]	0.077	0.000	0.055	0.154	[−0.075, 0.331]	0.100	0.942
COM:COP	0.245	−0.330 *	[−0.514, −0.126]	0.101	0.000	0.186	−0.275 *	[−0.438, −0.079]	0.091	0.003
FIN:NFCIR	0.138	0.364 *	[0.068, 0.622]	0.145	0.999	0.209	0.456 *	[0.097, 0.840]	0.205	1.000
OIL:PROD	0.129	−0.161 *	[−0.293, −0.028]	0.068	0.000	0.026	−0.084	[−0.194, 0.025]	0.056	0.000
FIN:NFCIC	0.088	0.425 *	[0.017, 0.809]	0.203	0.994	0.021	0.254	[−0.176, 0.645]	0.217	0.998
ACT:ADS	0.042	−0.006	[−0.012, 0.001]	0.003	0.010	0.185	0.007 *	[0.002, 0.011]	0.003	1.000
OIL:SPREAD	0.041	0.003	[0.000, 0.007]	0.002	1.000	0.032	0.003	[−0.001, 0.006]	0.002	1.000
ACT:BDI	0.031	0.026	[−0.011, 0.062]	0.019	0.987	0.993	0.063 *	[0.035, 0.091]	0.014	1.000
UNC:GVX	0.024	0.028	[−0.011, 0.066]	0.020	1.000	0.096	0.040 *	[0.004, 0.076]	0.019	1.000
UNC:USD	0.020	0.292	[−0.315, 0.875]	0.312	0.835	0.879	0.877 *	[0.411, 1.350]	0.240	1.000
OI:220618	0.019	−0.023	[−0.060, 0.014]	0.019	0.001	0.011	0.009	[−0.020, 0.037]	0.015	0.921
OIL:PRICES	0.019	0.013	[−0.010, 0.037]	0.012	0.992	1.000	−0.547 *	[−0.631, −0.465]	0.042	0.000
OC:061218	0.014	−0.017	[−0.052, 0.018]	0.018	0.000	0.011	−0.010	[−0.040, 0.020]	0.015	0.066
UNC:EPU	0.014	0.004	[−0.007, 0.015]	0.005	0.956	0.023	−0.006	[−0.014, 0.002]	0.004	0.001
OC:051219	0.013	0.017	[−0.018, 0.051]	0.017	1.000	0.010	−0.008	[−0.035, 0.020]	0.014	0.061
OE:010719	0.013	−0.014	[−0.049, 0.020]	0.018	0.001	0.856	−0.053 *	[−0.081, −0.024]	0.015	0.000
UNC:GSIG	0.011	−0.005	[−0.020, 0.011]	0.008	0.011	0.018	−0.009	[−0.024, 0.006]	0.008	0.002
OE:301117	0.009	−0.001	[−0.035, 0.034]	0.018	0.379	0.013	−0.012	[−0.039, 0.015]	0.014	0.004
OE:250517	0.009	0.002	[−0.032, 0.035]	0.017	0.610	0.016	0.015	[−0.012, 0.041]	0.014	1.000
(Intercept)	1.000	−0.002	[0.000, 0.000]	0.000	0.000	1.000	0.000	[0.000, 0.000]	0.000	0.000

Note: The table presents the estimation results for the fixed-effects panel models using Bayesian model averaging. The baseline sample of 36 firms and the baseline prior choice are considered. Abbreviations used: PIP—posterior inclusion probability, PM—posterior mean along with 95% confidence bands, PSD—posterior standard deviation, CPS—conditional positive sign statistic. Posterior mean and posterior standard deviation statistics were calculated conditional on the variable inclusion. Estimation is based on Markov chain Monte Carlo model composition (MC³) sampling with 1 million burn-in draws and 9 millions draws from the posterior distribution. Bold values indicate PIP values above 0.5. Effective determinants are denoted with an asterisk. For variables' definitions, transformations, categorization and sources, the reader is referred to Table 3.

For the overwhelming majority of variables with the PIPs exceeding 0.5 we show substantial evidence of robustness. In particular, we report that CDS spreads increase with rising historical volatility of oil prices, throughout recessions, along with increasing capacity utilization in the sector and with falling iron ore prices. For these variables the PIP oscillates around 0.9 which indicates

that they are included in around 90% of all posterior models. We also report that following the unprecedented cuts by the OPEC+ alliance, the default risk declined considerably as the market stabilized. However, the impact on CDS spreads is far smaller than that of the fiasco of the talks, which indicates a strongly asymmetric reaction of the market towards positive and negative news. This finding complements the results by Liu et al. [60] who show heterogeneous effect of OPEC announcements for crude oil prices. Next, we show that the overall financial conditions, the leverage situation, change in the broad index of industrial metal prices and the proxy for economic surprise also affect CDS spreads in line with the economic intuition. In particular, we report that tighter than average financial conditions and decreasing leverage result in increasing credit risk (although the evidence for the leverage situation is only weak). In turn, in case of the Citi Economic Surprise Index for Global Economy we show that positive surprises regarding the stance of the global economy tend to decrease the credit risk in the industry. It is also worth mentioning that the pledge by the OPEC+ to maintain production cut at a lower level since August 2020 somewhat increases the credit risk in the sector, but this variable enters the model far less frequently, while other decisions of the OPEC do not seem to affect the default risk of studied companies to a significant extent.

Figure 3 contains the graphical presentation of the discussed results. Apart from previously discussed findings, the plot also shows that in some models with relatively high PMP, we can observe that variables with similar information content are used interchangeably. This is the case for aluminium and copper prices which substitute occasionally the broad industrial metal price index. Likewise, the ANFCI index (adjusted to be uncorrelated with economic conditions) substitutes the baseline NFCI and leverage NFCIL indices. Finally, the figure shows that the best model includes in total 16 variables and accounts for around 4% of the PMP.

6. Sensitivity Analysis

To test the robustness of our results, we explore their sensitivity across two dimensions. Firstly, we check how different assumptions on the priors for the BMA model affect our conclusions regarding the robustness of the determinants of CDS spreads. Secondly, we investigate whether the latest period of the COVID-19 pandemic influences our estimates. This is motivated both by the extreme variations observed for the studied measure of the credit risk and the considerable volatility in explanatory variables at the end of our sample. In the next section, we provide additional evidence on the determinants of CDS spreads for a more homogeneous group of firms active in the shale sector in the North America.

Robustness with respect to prior assumptions. In the first step, we investigate whether the choice of the prior information affects our baseline results. To this end, we consider in total 15 different pairs of priors imposed upon the model and the estimation process, as discussed in Section 3.2. For each pair we re-estimate the model using the baseline sample and the full time span. Figure 4 presents the outcomes of this procedure by comparing the PIPs (the upper panel), standardized PMs and PSDs (middle panels) and the CPS statistics (bottom panel) across all considered possibilities.

The results of this exercise show that changing the prior information does not affect qualitatively the posterior estimates, especially for variables for which the PIP indicates either substantial or decisive evidence of robustness. That said, we observe significant dispersion of the PIPs for variables which are less likely to be considered in the baseline specification. This is especially vivid in the case of the empirical Bayes local g prior (EBL). Employing this approach results in an overall significant increase in the PIPs across all considered independent variables, an evidence in line with other empirical outcomes [36]. Thus, we conclude that the use of this prior may lead to the overparametrization of the model, thereby acting to the detriment of the BMA framework which aims at identifying a (narrow) set of robust determinants. In turn, setting the binomial model prior with more restrictive prior inclusion probability results in the most conservative estimate of PIPs, especially when the BRIC or the UIP prior for parameters is chosen. That said, a more stringent prior does not affect the PIPs for variables with either strong or decisive evidence of robustness. Further panels of Figure 4 indicate that the

choice of the prior assumptions have a negligible impact on other considered statistics. In fact, only the CPS measure for two variables with very low PIPs becomes less clear. We conclude that the choice of the model prior put forward by Ley and Steel [25] along with the BRIC prior by Fernández et al. [40] is robust. Thus, we argue that employing other priors, except for the empirical Bayes data-driven approach, does not affect our conclusions.

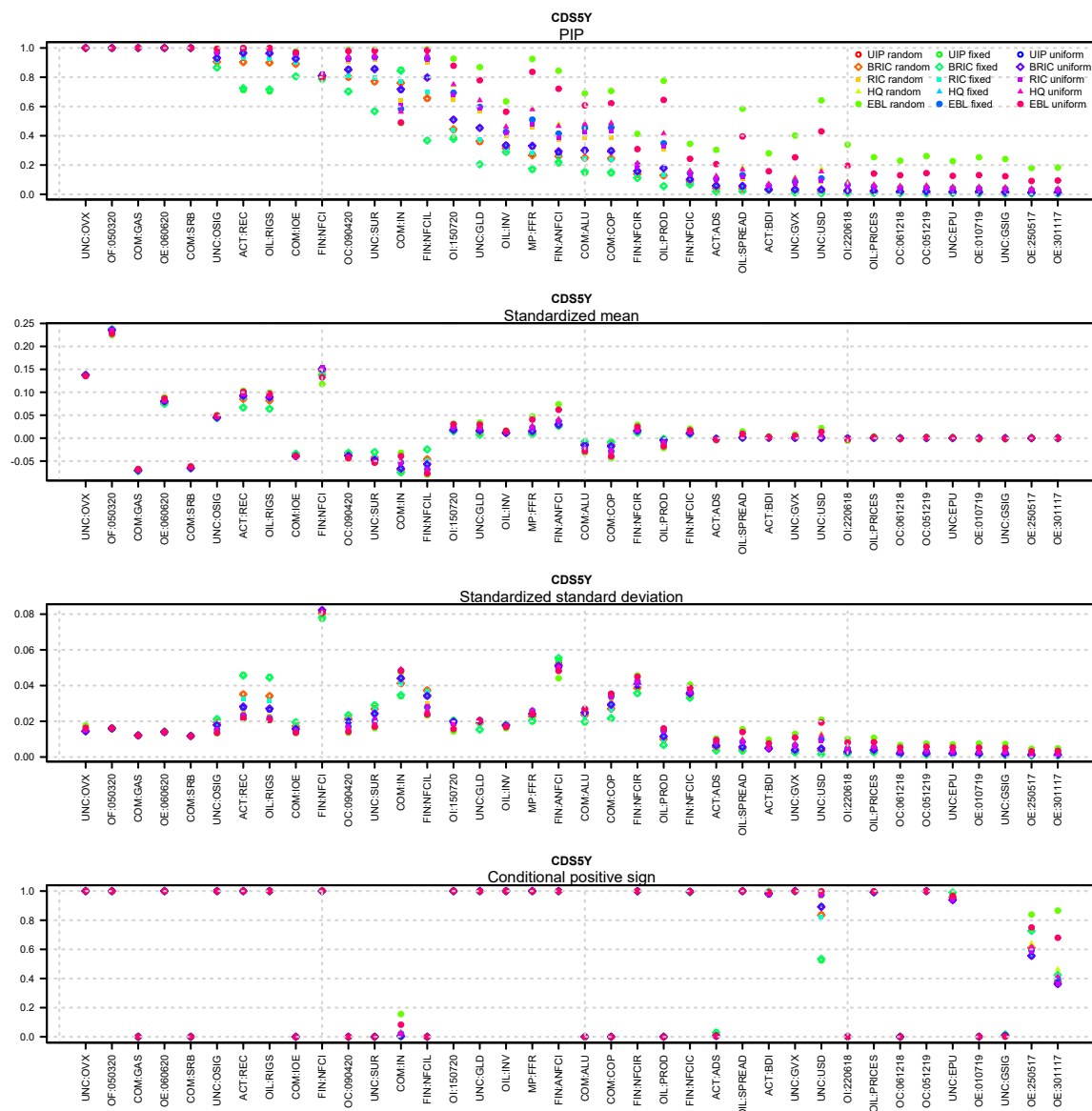


Figure 4. Sensitivity analysis with respect to the choice of prior information. Note: Figure 4 presents the results of the sensitivity analysis with respect to the choice of the prior information when the baseline sample of firms is considered. The first panel presents the PIP statistic across different priors chosen. The second panel illustrates the robustness of the posterior mean estimates, whereas the third panel shows the variability in the posterior standard deviation across alternative specifications. The last panel reports the conditional positive sign (CPS) statistic for all model setups. For variables' definitions, transformations, categorization and sources, the reader is referred to Table 3.

The impact of the COVID-19 outbreak. It goes without saying that the outbreak of the COVID-19 pandemic has affected most sectors of the global economy, the oil and gas industry included, as evidenced by Bouri et al. [4]. Figures 1 and 2 clearly indicate a period of excess variability in both CDS spreads and its potential determinants. Therefore, we check the robustness of the results with respect

to the choice of the sample. To this end, we restrict our sample and end it on the 29 December 2019, thereby precluding the outbreak of the COVID-19 pandemic and its macroeconomic and financial effects. This is a reasonable step as we expect a shift in the importance of factors affecting CDS spreads in the oil and gas sector in the North America following the coronavirus crisis. Moreover, performing subsample analysis seems most convenient and straightforward given the complexity of the BMA. Finally, running a separate analysis provides us with the sense of further robustness of our baseline results. On a side note, restricting the sample does not affect the precision of estimation since we use weekly data. The results of the estimation conducted on a shorter sample are presented in Table 5.

In this exercise we identify eleven variables as robust determinants of the CDS spreads. The evidence indicates their considerable robustness as key drivers of CDS spread fluctuations, as their PIPs exceed 0.85 in the majority of cases. On inspection, there are several discrepancies with respect to the results obtained for the full sample. First, a major difference is that the oil prices enter every specification of the model with a negative sign. This indicates that in normal times with decreasing oil prices, the credit risk of oil and gas firms increases, as predominantly lowering prices of this commodity negatively affect the profitability of those firms. On the other hand, when considering the full sample, the level of oil prices cease to be a robust determinant of CDS spreads, as factors indirectly related to the price of this commodity and its variability became much more important in explaining the variation in the dependent variable. The short sample results also corroborate the role of natural gas prices in driving the credit risk.

During normal times we observe that in fact more risk channels exert a statistically significant impact on credit risk. The results indicate that the risk channel is captured by various proxies related to the (i) oil market idiosyncratic factors (measured by the implied oil price volatility), (ii) global demand shocks (proxied by macroeconomic surprises) and (iii) broad, market-based risk aversion (measured by the flight to safe have assets like gold or the dollar). These factors exert a significant impact on CDS spreads. Next, given the shorter sample, by construction we do not observe several large effects related to the decisions introduced by the OPEC in 2020. However, we show that extending the oil cuts in July 2019 had a negative effect on credit risk for the studied firms. This can be interpreted that the financial market has discounted the pledge for smaller supply by the OPEC countries as a factor affecting positively the profitability of oil firms, thereby downgrading their default risk. We validate also the importance of the factors related to the overall financial conditions in the economy in shaping CDS spreads. As regards the link between CDS spreads and industrial metal prices, we show that during normal times this nexus is slightly more robust, with the PIP exceeding 0.80, while the development in specific industrial metal prices loses considerably on significance. Finally, a caveat should be aired here, as an increase in freight costs (a proxy for real activity in the global economy) exerts a significant, positive impact on CDS spreads. This particular result stands at odds with our intuition, since improving global demand should translate into higher demand for oil and procure a rise in oil prices, thereby lowering the risk of default for oil firms. However, given the recent criticism of demand measures based on the shipping costs [61], we do not put much emphasis on this particular result.

7. Shale Oil and Gas Firms

In this section we provide additional evidence by investigating the determinants of CDS spreads for the shale oil and gas industry. To this end, we narrow down the baseline sample to 21 firms at least partly active in the shale sector, as in the second row of Table 1. The BMA results obtained for the full sample and the shale sample are reported in Table 6. To facilitate comparison, all coefficients are standardized, which effectively brings down the data to the same order of magnitude.

Even though the firms involved in shale oil and gas activity arguably carry the bulk of the credit risk of the entire oil and gas industry, the results for both samples are rather similar, in terms of PIPs and the standardized coefficient values as well. In particular, we observe that for variables with decisive evidence of robustness in the baseline sample the PIPs and PMs are similar in the shale sample. An exception from this rule can be noticed for several variables denoting OPEC decisions. We observe

that following the introduction of the production cuts, the credit risk in the shale sample has decreased more markedly. Moreover, extending the limits in June 2020 followed by the promise to slowly increase production have a more significant effect on CDS spreads. This suggests that the sensitivity of the shale firms to the OPEC decisions is stronger. Additionally, several variables are evidenced in the baseline but not shale sample. These are the historical volatility of oil prices and iron ore futures prices. The informational content of the latter two is to some extent shared by the implied volatility of oil prices and industrial metal index, which are among most evident variables in the shale sample. Additionally, we provide evidence that for shale companies the recession indicators are not significant. Strikingly, so is the change in the capacity utilization in the US. This suggests that the domestic activity is not as important as the global supply determined by the OPEC+ members.

Table 6. BMA results for the shale sample and the baseline sample.

Variable	Shale Sample (8 January 2017–2 August 2020)					Baseline Sample (8 January 2017–2 August 2020)				
	PIP	PM	PM Conf. bd.	PSD	CPS	PIP	PM	PM Conf. bd.	PSD	CPS
UNC:OVX	1.000	0.119 *	[0.083, 0.158]	0.019	1.000	1.000	0.138 *	[0.110, 0.166]	0.014	1.000
OF:050320	1.000	0.226 *	[0.185, 0.263]	0.020	1.000	1.000	0.236 *	[0.203, 0.266]	0.016	1.000
OE:060620	1.000	0.099 *	[0.065, 0.131]	0.017	1.000	1.000	0.079 *	[0.050, 0.106]	0.014	1.000
COM:SRB	0.999	−0.074 *	[−0.104, −0.044]	0.015	0.000	1.000	−0.065 *	[−0.089, −0.042]	0.012	0.000
OC:090420	0.998	−0.078 *	[−0.110, −0.046]	0.016	0.000	0.804	−0.045 *	[−0.070, −0.020]	0.013	0.000
OI:150720	0.995	0.074 *	[0.042, 0.104]	0.016	1.000	0.445	0.037 *	[0.013, 0.061]	0.012	1.000
COM:GAS	0.987	−0.065 *	[−0.095, −0.035]	0.015	0.000	1.000	−0.071 *	[−0.095, −0.047]	0.012	0.000
UNC:GLD	0.967	0.064 *	[0.033, 0.095]	0.016	1.000	0.363	0.036 *	[0.012, 0.061]	0.013	1.000
COM:IN	0.928	−0.108 *	[−0.141, −0.072]	0.018	0.000	0.761	−0.091 *	[−0.119, −0.062]	0.016	0.003
UNC:SUR	0.851	−0.071 *	[−0.106, −0.033]	0.018	0.000	0.772	−0.055 *	[−0.085, −0.024]	0.016	0.000
FIN:NFCI	0.774	0.183 *	[0.080, 0.253]	0.038	1.000	0.809	0.182 *	[0.091, 0.249]	0.041	1.000
COM:IOE	0.401	−0.044 *	[−0.073, −0.015]	0.015	0.000	0.891	−0.042 *	[−0.065, −0.020]	0.011	0.000
FIN:ANFCI	0.304	0.143 *	[0.034, 0.235]	0.059	1.000	0.259	0.106 *	[0.025, 0.195]	0.043	1.000
ACT:REC	0.229	0.058	[0.012, 0.129]	0.031	1.000	0.903	0.095 *	[0.051, 0.139]	0.022	1.000
UNC:OSIG	0.160	0.040 *	[0.008, 0.072]	0.016	1.000	0.906	0.049 *	[0.023, 0.076]	0.014	1.000
FIN:NFCIC	0.096	0.118 *	[0.004, 0.216]	0.058	0.999	0.088	0.110 *	[0.004, 0.209]	0.053	0.994
COM:ALU	0.087	−0.065 *	[−0.109, −0.004]	0.026	0.000	0.250	−0.051 *	[−0.080, −0.018]	0.016	0.000
FIN:NFCIL	0.085	−0.060 *	[−0.113, −0.005]	0.027	0.002	0.658	−0.070 *	[−0.111, −0.029]	0.021	0.000
OIL:RIGS	0.080	0.068 *	[−0.009, 0.127]	0.034	0.951	0.900	0.091 *	[0.050, 0.133]	0.021	1.000
OIL:INV	0.078	0.035 *	[0.003, 0.066]	0.016	1.000	0.314	0.035 *	[0.011, 0.060]	0.013	1.000
OIL:PROD	0.061	−0.030	[−0.059, −0.001]	0.015	0.000	0.129	−0.027 *	[−0.050, −0.005]	0.012	0.000
COM:COP	0.054	−0.056	[−0.104, 0.022]	0.031	0.038	0.245	−0.059 *	[−0.093, −0.023]	0.018	0.000
OIL:SPREAD	0.052	0.030	[−0.001, 0.059]	0.015	1.000	0.041	0.021	[−0.002, 0.045]	0.012	1.000
ACT:BDI	0.043	0.032	[−0.006, 0.066]	0.018	0.994	0.031	0.023	[−0.009, 0.054]	0.016	0.987
FIN:NFCIR	0.034	0.067	[−0.069, 0.180]	0.058	0.859	0.138	0.103 *	[0.019, 0.176]	0.041	0.999
OIL:PRICES	0.032	0.034	[−0.007, 0.074]	0.021	1.000	0.019	0.020	[−0.014, 0.055]	0.018	0.992
MP:FFR	0.025	0.034	[−0.019, 0.086]	0.028	0.948	0.267	0.047 *	[0.013, 0.081]	0.018	1.000
OC:061218	0.019	−0.019	[−0.047, 0.010]	0.015	0.000	0.014	−0.011	[−0.033, 0.011]	0.011	0.000
UNC:EPU	0.014	0.015	[−0.016, 0.047]	0.016	0.999	0.014	0.010	[−0.015, 0.035]	0.013	0.956
OI:220618	0.013	−0.012	[−0.042, 0.017]	0.015	0.001	0.019	−0.015	[−0.039, 0.009]	0.012	0.001
OE:010719	0.012	−0.012	[−0.040, 0.016]	0.014	0.002	0.013	−0.009	[−0.031, 0.013]	0.011	0.001
ACT:ADS	0.012	−0.008	[−0.050, 0.031]	0.021	0.390	0.042	−0.024	[−0.050, 0.003]	0.014	0.010
OE:301117	0.011	−0.011	[−0.039, 0.017]	0.014	0.009	0.009	−0.001	[−0.023, 0.021]	0.011	0.379
OC:051219	0.011	0.010	[−0.019, 0.039]	0.015	1.000	0.013	0.011	[−0.011, 0.032]	0.011	1.000
UNC:USD	0.010	0.005	[−0.039, 0.043]	0.021	0.903	0.020	0.017	[−0.019, 0.053]	0.019	0.835
UNC:GVX	0.010	0.009	[−0.023, 0.040]	0.016	0.972	0.024	0.018	[−0.008, 0.044]	0.013	1.000
UNC:GSIG	0.009	0.002	[−0.028, 0.031]	0.015	0.526	0.011	−0.007	[−0.029, 0.016]	0.012	0.011
OE:250517	0.009	0.000	[−0.027, 0.028]	0.014	0.464	0.009	0.001	[−0.020, 0.022]	0.011	0.610
(Intercept)	1.000	−0.023	[0.000, 0.000]	0.000	0.000	1.000	−0.022	[0.000, 0.000]	0.000	0.000

Note: The table presents the BMA estimation results of the fixed-effects panel models for the alternative sample of 21 firms involved in shale oil and gas in comparison to the full baseline sample of 36 firms, both with the baseline prior choice. The estimation period spans from 8 January 2017 to 2 August 2020. In the table all statistics are standardized to facilitate comparison. Bold values indicate PIP values above 0.5. Effective determinants are denoted with an asterisk. Abbreviations and notational conventions as in Table 5.

In summary, we can state that the interpretation of BMA estimates from Section 5 holds essentially regardless of the composition of the sample. We identify major OPEC decisions and the implied volatility of oil prices coupled with change in the natural gas prices as variables with decisive evidence of robustness. We also evidence that prices of industrial metals and financial conditions proxy are important indicators for the development in CDS spreads in the oil and gas industry.

8. Conclusions

The outbreak of the COVID-19 pandemic has uncovered a significant default risk for firms active in the oil and gas market in the North America. Following the unprecedented decline in real activity across the globe in the first half of 2020 due to severe lockdowns introduced in a number of economies the global demand for oil plummeted, with prices tumbling since late February 2020 to the lowest level since the end of the previous century. These developments have particularly heavily impacted the firms active in the oil and gas market in the US and Canada, with the phantom of bankruptcy menacing over the industry. The significant rise in the default risk is exemplified by the sharp increase in CDS spreads issued for the bond-related liabilities of these firms. From both the market and the academic perspective, the current developments have reinforced the need to better understand the sources of the fluctuations in these instruments. In this paper we attempt to establish the determinants of fluctuations in CDS spreads for the firms within the oil and gas industry in the North America.

Given the limited theoretical guidelines on the determinants of CDS spreads, we chose Bayesian model averaging, an approach providing a robust framework for inference whenever the model specification uncertainty is overwhelming and the researcher is confronted with the proliferation of possible explanatory variables. Using robust Bayesian inference we derive posterior probability for both considered regressors and each model. Therefore, as we essentially incorporate the information from every possible empirical model that can be constructed from a predetermined set of variables, we avoid probable misspecification issues arising when inferring from a subjectively chosen model or data-mining concerns.

We contribute to the literature by identifying a set of robust determinants of CDS spreads issued for the oil and gas firms operating in the North America. We also uncover which factors have considerable explanatory power for CDS spreads issued for a subset of firms active in the shale sector. The outcomes of the BMA estimation show that oil price volatility positively affect the market view of the credit risk of oil and gas companies in the North America. Moreover, major adjustments in the supply policy by the OPEC affects CDS spreads to a considerable extent. In particular, the recent fiasco of the talks between OPEC and leading non-OPEC producers and exporters has significantly increased the credit risk, whereas unprecedented oil supply cuts resulted in its fall, albeit to a much smaller extent. Given the recent decoupling of natural gas and oil prices, we show that the fluctuation in prices of both these commodities is important for CDS spreads in the sector, at least during normal times. Furthermore, the situation in the industrial metal markets arguably correlates negatively with the CDS spreads, as the prices of industrial metals are considered a good high-frequency proxy for the global economic stance. Finally, we show that both the overall financial conditions in the US and various channels related to the global and sectoral uncertainty or risk aversion influence significantly the development in CDS spreads. The overall robustness of our results are demonstrated by sensitivity analyses, which also reveal that prior to the outburst of the COVID-19 pandemic oil prices have been among decisive determinants of CDS spreads. Finally, the interpretation of the results holds regardless of the considered sample of firms.

We believe that the paper provides interesting insights into the determinants of the credit risk in the oil and gas sector in the North America. However, it does not discuss four issues. First, the paper remains mute on whether the use of the identified robust determinants leads to superior explanatory power in predicting the changes in CDS spreads out-of-sample. Second, we do not discuss the advantages of the shrinkage the Bayesian model averaging provides in the forecasting context. Third, models with non-linear effects and heavy tails are not included in the space of explored specifications. Yet, given recent extreme market variations it would be interesting to enhance model specifications by effects accounting for conditional volatility, leverage and non-normal distribution assumptions. Finally, we do not discuss to what extent specific features of oil and gas companies, such as their size or financial conditions, relate to the credit risk and how differentiated the reaction of CDS spreads following common market developments can be. These issues provide new interesting avenues for future research.

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