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Understanding corporate debt from the oil market perspective

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A B S T R A C T

We design and test the hypothesis that for energy firms' oil market activities impact capital structure. Using a unique sample of 726 energy firms from 56 countries, we find that oil market activities do influence capital structure. The speed of adjustment (SOA) to leverage when not exposed to oil market activities is between 27.5 and 66.4%. When exposed to oil price growth (market liquidity) the corresponding SOA is between 51.1 and 72.4% (40.9–76.1%). We conclude that oil price growth slows down while market liquidity improves SOA to leverage for energy firms. By comparison, using a sample of over 32,000 non-energy firms from 108 countries, we find no evidence that oil market activities dictate capital structure.

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1. Introduction

Our goal in this paper is to revisit the issue of the relevance of capital structure trade-off theory but from an energy market point of view. With respect to the vast literature (see Fama and French, 2002; Flannery and Rangan, 2006; and Shyam-Sunder and Myers, 1999) on trade-off theory, our position is novel and different in the following way. Motivated by the fact oil companies are different from non-oil companies (see Section 2), we ask what precisely the role of oil market activities is. Oil market activities are an important consideration because they create market imperfections (see Section 2 for a detailed discussion on this). For energy firms, oil prices and related measures, such as price basis and price return volatility, constitute key sources of information asymmetry. Energy firms are highly leveraged compared to non-energy firms (see Kim and Choi, 2019; Pierru et al., 2013). Yet, the fact that the role of oil market activities in shaping a firm's capital structure has not been studied represents a research gap worthy of investigation. Doing so will allow us to understand capital structure from a different (oil market) point of view.

Our paper, therefore, is a response to this research gap. Precisely for this reason, we consider energy firms because they are the most directly impacted by oil prices (see Narayan and Sharma, 2011). We collect a sample of energy firms that belongs to 56 countries. We have annual data over the 1988 to 2015 period for 726 firms, totaling no less than 8641 firm-year observations. The sample is unique because it represents the first study on capital structure of energy firms and rich because it considers data from 56 countries. We, therefore, have a global sample. We do not ignore non-energy firms because nothing is known about how their SOA reacts to oil market activities. We do compile a large sample (32,382 firms from 108 countries) of global non-energy firms and, in additional results (see Section 5), examine whether oil market activities influence their SOA. The inspiration for studying capital structure in this comparative manner has roots in the data. See, for instance, Fig. 1 which plots equal-weighted time-series (1988–2015) data on market debt ratio (MDR) for energy (mdr_e) and non-energy (mdr_ne) firms against the West Texas Intermediate (WTI) oil price. The visual interpretation is that the WTI-mdr_e and WTI-mdr_ne have co-moved differently over the 1988 to 2015 period. There has been a stronger connection between WTI and mdr_e compared to WTI and mdr_ne. Unconditional correlations also confirm this: WTI-mdr_e (0.40, t-stat = 2.22) is twice as much correlated compared to WTI-mdr_ne (0.20, t-stat. = 1.05). Indeed, the WTI-mdr_ne correlation is statistically insignificant. The implication is that SOA to leverage for energy firms when exposed to oil market activities is likely to be different compared to non-energy firms. What precisely is the difference constitutes the subject of this paper.

Our main story revolves around using oil market activities to test the hypothesis that they matter to leverage and the speed at which leverage reverts to equilibrium. Together, broadly, we consider eight measures, namely, oil spot/futures price growth, their volatility, basis, volume of trade, liquidity (open interest), and the US$100 oil price psychological barrier, to represent oil market activities. We proxy oil prices with the annual growth rate in oil prices. As an alternative measure of the effect of oil prices, we consider the psychological barrier effect—that is, the

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The remainder of the paper proceeds as follows. Section 2 contains the motivation of this paper’s hypothesis that oil market activities matter to leverage of oil firms. Section 3 presents the data and discusses results. Section 4 discusses the results from robustness tests. Section 5 contains additional results focusing on the effect of oil market activities on non-energy firms and on controlling for country effects in panel regressions. The final section provides concluding remarks.

2. Motivation: Why capital structure of energy firms is different?

2.1. How the oil market is different from other markets from a debt point of view?

The work of Kim and Choi (2019) provides an excellent description of how and why the debt leverage situation of oil and gas companies are likely to be different. In their story, the explanation is that oil projects are risky investments, which require large amounts of capital. This capital requirement implies higher borrowings meaning higher debt. Typically for oil companies, the borrowing has to be external given that internal sources of financing maybe limited given liquidity and cash flow constraints associated particularly with medium to large scale projects.

With oil companies, a common way of financing large projects is through project finance (see Perru et al., 2013). Several studies show that project financing-based projects are highly leveraged compared to non-project financed ones (Shah and Thakor, 1987). Projects associated with project financing mechanism of funding have loans that carry lower credit margins (Kleimeier and Megginson, 2001) compared to non-project financed ones.

These studies suggest that oil companies if they are financed by project financing are likely to be highly leveraged. This is one way oil companies differ from non-oil companies.

There is also a second way oil companies are different from non-oil companies. This reason has roots in shocks faced by firms. With oil companies, oil price shocks can be devastating to their liquidity and cash flow positions more than oil price shocks are to non-oil firms. The literature argues that severe oil price shocks and global recessions which drive down oil prices represent liquidity and cash flow stress for oil firms (see Korotin et al., 2017; Teti et al., 2020). Korotin et al. (2017), for instance, argue that during severe oil prices decline, oil companies refinancing becomes extremely costly. Teti et al. (2020) demonstrates this point more concretely. They consider the effect of oil price fall from US$115/barrel in June 2014 to <US$35/barrel in February 2016. They show that this sharp and sudden fall in oil price made oil and gas industry more vulnerable hence riskier. As riskiness rises, credit ratings decline, making external borrowing costlier.

Finally, there is a possibility that debt is used for greater resource utilization. To this effect, Filbeck and Gorman (2000) argue that firms use debt to achieve optimal asset utilization. They find a positive association between leverage and asset utilization for resource intensive commodities. We infer that given oil is also a resource intensive commodity, oil companies may be using debt to maximize resource usage optimality. In this way, at least a possibility exists for oil-based companies to explore resource optimality via debt which distinguishes them from non-oil companies.

2.2. The relevance of oil market activities for corporate debt leverage

Our argument and hence hypothesis is that oil market activities matter to corporate capital structure of energy firms. The speed at which energy firms adjust their leverage depends on the evolution of this oil price—both its first and second order moments, volume of oil contracts traded, liquidity in the oil market and the price basis. There are several channels through which the oil market related activities introduce information asymmetry and transaction costs to energy firms. The starting point is to recognize that there are two types of traders in the
oil market—hedgers and speculators. A key characteristic of speculators is that they possess different information on selected variables. To avoid strategic participation in the spot market, Perrakis and Khoury (1998) assume that speculators only participate in the futures market while speculators and hedgers both are active in the spot market. Hedgers are generally less well informed but possess private information (Johnson, 1960) but they do not possess private information sufficient to impact futures market equilibrium (Perrakis and Khoury, 1998). Speculators derive information from the informational asymmetry and randomness of the spot market supplies (see Grossman, 1978; Bray, 1981). The key message of this discussion is that because hedgers and speculators take positions in both spot and futures markets and each possesses different degree of information, a source of information asymmetry in the oil market is hedgers and speculators themselves.

A second channel of information asymmetry is informational frictions in commodity markets, a subject that is illustrated neatly in Sockin and Xiong (2015). The key message of this paper is that commodity market participants are exposed to severe informational frictions regarding global supply, demand and inventory of these commodities. They attribute this to the greater global importance (hence globalization) of crude oil. The theoretical model of Sockin and Xiong (2015) has several unique features, from which we can infer and generalize that: (1) a higher oil price reflects a stronger global economy, enticing producers to increase oil production; (2) an oil supply shock constitutes information noise, thereby oil price does not fully reveal the strength of the global economy; and (3) because the futures market attracts different participants than the spot market, it may have its own informational effects on commodity demand and the spot price.

There is empirical support for point (3) also. There is, for instance, disagreement about future oil prices by professional market participants. As shown in Singleton (2011), the time-series dispersion in the standard deviation of the one-year ahead forecasts of oil prices by the professionals surveyed by Consensus Economics and the level of WTI oil prices has widened. This reflects information asymmetry in the oil market.

Oil market liquidity can obviate information asymmetry and transaction costs. Futures market open interest—our measure of oil market liquidity—reveals the number of outstanding contracts that are active. A high number of open interest implies higher volume of market participants, which reduces information asymmetry and transaction costs. From the work of Easley et al. (1996), we learn that higher trading volume is associated with higher probability of informed trading and higher intensity of informed and uninformed trading. They point out that higher liquidity tends to attract more uninformed traders compared to informed traders. In other words, while higher volume sees both informed and uninformed trading increase, liquidity has a larger effect on uninformed trading, thus it is easy to follow how liquidity reduces information asymmetry. Moreover, from the work of Edmans (2009), it is clear that increasing rate of liquidity can lower transaction costs.

### 3. Data and main results

#### 3.1. Data

We use two types of data to test our proposed hypotheses. First is the corporate leverage related data for energy firms and non-energy firms (see Section 5). A list of all variables used are noted in column 2 of Table 1. Book debt ratio (BDR) and MDR are used as dependent variables. A range of control variables, such as profitability (EBIT_TA), depreciation (DEP_TA), total assets (SIZE), fixed asset proportion (FA_TA), and research and development variables (R&D_TA) are used. Full details are provided in Table 1. These data are downloaded from the Compustat database. The second data series is with respect to crude oil; we use both the WTI and the Brent crude oil price as a proxy for the spot market. We use Brent crude oil data to identify dates on which the oil price reached the US$100 per barrel mark. Using these dates, we form a dummy variable to capture the oil price psychological barrier effect. This data are from the US Energy Information Administration website. We obtain the oil price futures, contracts traded (volume) and open interest data from the Commodity Research Bureau database. Finally, we use a GARCH (1,1) model to estimate oil price spot and futures price return volatility.

The specific steps involved in data construction are noted in Table 2. These can be summarized as follows. We begin by considering energy firms from the Compustat database. We specifically consider SIC codes 1311 (crude petroleum & natural gas), 1381 (drilling oil and gas wells), 1382 (oil & gas field exploration services), and 1389 (oil & gas field services). We consider a period 1988 to 2015 because it allowed

### Table 1

| Variable | Definition | N | Minimum | Maximum | Mean | SD |
|----------|------------|---|---------|---------|------|----|
| MDR      | Market debt ratio = book value of (short-term plus long-term) debt (Compustat items [9] + [34])/market value of assets (Compustat items [9] + [34] + [199] [25]). | 6303 | 0 | 0.878 | 0.170 | 0.218 |
| BDR      | Book debt ratio: (long-term [9] + short-term [34] debt)/total assets [6]. | 6303 | 0 | 0.945 | 0.179 | 0.215 |
| EBIT_TA  | Profitability: earnings before interest and taxes (Compustat items [18] + [15] + [16])/total assets (Compustat item [6]). | 6303 | −2.850 | 0.461 | −0.097 | 0.424 |
| MB       | Market to book ratio of assets: book liabilities plus market value of equity (Compustat items [9] + [34] + [10] + [199] [25])/total assets (Compustat item [6]). | 6303 | 0.142 | 69.749 | 2.773 | 7.872 |
| DEP_TA   | Depreciation (Compustat item [14])/total assets (Compustat item [6]). | 6303 | 0 | 0.290 | 0.043 | 0.051 |
| SIZE     | Log (total asset). | 6303 | 0 | 14.994 | 5.682 | 3.126 |
| FA_TA    | Fixed asset proportion: property, plant, and equipment (Compustat item [14])/total assets (Compustat item [6]). | 6303 | 0 | 0.551 | 0.439 | 0.296 |
| R&D_TA   | R&D expenses (Compustat item [46])/total assets (Compustat item [6]). | 716 | 0 | 0.535 | 0.021 | 0.066 |
| IND_MED  | Dummy variable equal to one if firm did not report R&D expenses and zero otherwise. | 6303 | 0 | 1.000 | 0.887 | 0.317 |
| INCR_MDR | Median industry MDR, calculated for each year based on the GIC industry groups. | 6303 | 0 | 0.441 | 0.088 | 0.099 |
| CROP     | Growth rate of Brent/WTI oil spot price (p), computed as p(t)−p(t−1)/p(t−1)*100. | 32 | −45.446 | 54.019 | 4.754 | 24.189 |
| CROP_FUTURE | Growth rate of oil futures price (p) computed as p(t−1)/p(t−1)−1*100. | 32 | −44.587 | 51.588 | 4.659 | 23.607 |
| VAR_SPOT | Volatility of spot price return computed using a GARCH (1,1) model. | 32 | 0.530 | 1.820 | 0.881 | 0.283 |
| VAR_FUTURE | Volatility of futures price return computed using a GARCH (1,1) model. | 32 | 0.463 | 1.609 | 0.765 | 0.250 |
| VOL_GROWTH | Growth in the number of contracts traded per annum. | 32 | −26.803 | 143.968 | 18.727 | 31.951 |
| OIL_GROWTH | Open interest growth: growth in the total number of outstanding contracts that are held by market participants per annum. | 32 | −22.436 | 136.933 | 16.678 | 28.439 |
| BASIS    | Crude oil spot price less crude oil futures price. | 32 | −1.325 | 0.715 | −0.028 | 0.494 |

This table provides information about variables, number of observation (N), and basic statistics, such as the minimum, maximum, mean and standard deviation (SD), for each variable used in our empirical analysis. The firm-level data are obtained from the Compustat database, while the source of Brent/ West Texas Intermediate spot price is the US Energy Information Administration website (EIA). We obtain the oil price futures, contracts traded (volume), and open interest data from the Commodity Research Bureau database.
us to maximize the number of countries for which we could obtain data. This period contains data for 56 countries and has 726 firms for a total of 8641 firm-year observations. We remove firms with at least two years of missing data and we winorize data at the 1% and 99% levels to remove outliers. This financial data are supplemented with the securities price data for the corresponding firms, as listed in Table 1.

Table 1 presents descriptive statistics of the data. Our main interest variables are MDR and BDR. The literature uses both measures of leverage as a dependent variable, although in testing the trade-off theory MDR is the preferred dependent variable. The difference between the two is that MDR is forward looking (accounts instantaneously for all information available through the financial market), whereas BDR is a historical accounting-based measure, implying that firm management may have an influence on the reported figures. By definition, therefore, MDR is expected to be more volatile than BDR. This is what we find as reported in Table 1. The standard deviation of MDR is at most 0.218 while that of BDR is 0.215 for the sample of entire 756 firms.

Appendix A contains a plot of the seven time-series oil market activity variables and a table of descriptive statistics. These provide a snapshot of the data series with respect to the oil market activity. Some key features of the data are as follows. Annual average growth rates in trading volume and open interest have been highest at 18.7% and 16.7%, respectively. This is followed by spot price growth (6.3%) and futures price growth (4.7%). These four series with the highest growth are also amongst the most volatile. In terms of persistence, the Dickey-Fuller unit root test, which examines the null hypothesis of a unit root, is reported in the last column of Table A1. The t-statistic reported in parenthesis suggests that the unit root null hypothesis can be rejected at the 5% level or better for all seven series. It is, therefore, clear that all series are stationary. We also observe that, based on the first-order autoregressive coefficient, there is some level of persistence in series such as basis, open interest and volume growth but they are all less than 0.43. The implication is that these series are statistically suitable for our regression analysis.

3.2. Empirical design

The empirical specification for a partial SOA to leverage (MDR) model widely used in the literature (e.g., Flannery and Rangan, 2006) has the following form:

\[ MDR_{it+1} = (1-\gamma)MDR_{it} + \gamma \beta X_{it} + \gamma \alpha t + \epsilon_{it+1} \]  

(1)

where \( \gamma \) is the SOA coefficient and MDR (or BDR in models for robustness/additional tests) proxies leverage. A range of theoretically motivated variables that help explain MDR is represented by \( X \) (see Table 1). These variables are common in this literature and, therefore, we refrain from repeating a discussion on them. A final note concerns the time it takes to achieve target leverage: From the estimates of the SOA, we compute the implied half-life as \( \log(0.5)/ \log(1 - \gamma) \), which is the number of years it takes to revert to half of the target level.

The regression model is estimated using five estimators, namely, the FE, LSDVC, BC, LD, and GMM. The idea behind reporting results from multiple estimators is to judge the robustness of the results from the estimator point of view. We will, however, use the difference GMM estimator as our preferred estimator for making general inference since it is the most widely used estimator.

4. Results

4.1. Oil spot and futures price effects

We begin with the results reported in Table 3 without oil market activity variables. We consider this regression as our baseline model, allowing us to compare SOA when oil market activity variables are included (Table 3). Across the five estimators, the coefficient on the one-period-lagged MDR falls in the 0.275 (t-statistic = 5.22) to 0.664 (t-statistic = 6.04) range. This result suggests a SOA of 33.6–72.5%. With our preferred estimator, GMM, the SOA is 72.5%, which translates to a half-life of 0.54 years. Across all other estimators, the half-lives are in the 0.99–1.69 years range. These results imply a fast rate of adjustment to leverage consistent with the trade-off theory.

We now examine results from the regression model where we include the growth rate in oil spot price (Table 3). We see that the SOA is slightly slower now in the range of 27.6–43.1%, with half-lives of between 1.08 years to 2.15 years. When we include an oil price dummy variable capturing the psychological effect of price reaching the US $100 per barrel mark (Table 3), we again observe half-lives higher (in the 0.94 years to 1.85 years range) than when oil effects are excluded. These results are consistent with Hypothesis 1. They imply that oil prices by introducing information asymmetry delay SOA to leverage for energy firms.

Oil price futures effect on SOA is reported in Panel B of Table 4. We see that across all estimators the slope coefficient on oil price futures growth rate is statistically different from zero. The t-statistic (in absolute terms) is in the 2.30 and 4.43 range. The effect is negative suggesting that like spot oil price growth the futures price growth reduces debt. However, we do not observe any remarkable difference in SOA. The half-lives are within the 0.81 to 1.53 years range.

Finally, we consider basis, which is the difference between spot and futures oil price. The results are reported in Panel C (Table 4). Across all five models, basis is statistically insignificant. The t-statistic is in the 0.28 to 1.29 range.

4.2. Oil price volatility effects

Oil price spot and futures volatility also represents asymmetry in the oil market. This sub-section is devoted to understanding precisely the role of price volatilities in influencing SOA. The results are reported in Panel D (spot price return volatility) and Panel E (futures price return volatility) of Table 4. Prices volatilities are bad for debt; they increase debt. All estimators suggest that a rise in price volatilities increases debt by between 0.048% and 0.056% (spot price volatility) and by
## Table 3
Regression results.

| FF  | 1   | 2   | 3   | LSDVC | 4   | 5   | 6   | BC   | 7   | 8   | 9   | LD   | 10  | 11  | 12  | Difference GMM |
|-----|-----|-----|-----|-------|-----|-----|-----|------|-----|-----|-----|------|-----|-----|-----|----------------|
| **MDR** | 0.479*** | 0.511*** | 0.418*** | (10.02) | 0.418*** | 0.680*** | 0.644*** | (11.02) | 0.664*** | 0.724*** | 0.688*** | (6.04) | 0.560*** | 0.526*** | 0.557*** | 0.275*** | 0.569*** | 0.534*** |
| **GOP_SPOT** | -0.0008*** | -0.0009*** | -0.0009*** | (-5.18) | -0.0009*** | -0.0009*** | -0.0007*** | (-5.29) | -0.0009*** | -0.0009*** | -0.0009*** | (-3.96) | -0.0009*** | -0.0009*** | -0.0009*** | -0.0009*** | -0.0009*** | -0.0009*** |
| **D_OIL** | -0.026 | -0.027 | -0.027 | (−2.54) | -0.026 | -0.027 | -0.027 | (−2.36) | -0.038 | -0.007 | -0.018 | (−2.48) | -0.028 | -0.041 | -0.026 | (−1.14) | -0.061 | -0.025 | -0.022 |
| **EBIT_TA** | -0.026 | -0.017 | -0.027 | (−2.54) | -0.026 | -0.017 | -0.027 | (−2.36) | -0.038 | -0.013 | -0.022 | (−2.48) | -0.028 | -0.037 | -0.026 | (−1.14) | -0.061 | -0.025 | -0.022 |
| **MB** | 0.001 | 0.002 | 0.002 | (0.55) | 0.001 | 0.003 | 0.002 | (0.55) | 0.002 | 0.004 | 0.000 | (0.55) | 0.003 | 0.003 | 0.003*** | (0.55) | 0.002 | -0.002 | -0.003 |
| **DEP_TA** | -0.070 | 0.144 | 0.087 | (-0.34) | -0.070 | 0.144 | 0.087 | (-0.34) | -0.211 | -0.182 | -0.114 | (-0.34) | -0.343 | -0.326 | -0.234 | (-0.34) | -1.085*** | -1.077*** | -1.11*** | -0.997 | -0.262 | -0.322** |
| **Size** | 0.039*** | 0.028*** | 0.042*** | (4.64) | 0.039*** | 0.028*** | 0.042*** | (4.64) | -0.387 | -0.76 | -0.46 | (-0.387) | -0.76 | -0.46 | -0.7 | (-0.387) | -3.56 | -3.35 | -3.58 | (-0.387) | -1.50 | -1.84 |
| **FA_TA** | 0.079* | 0.091** | 0.070 | (1.68) | 0.079* | 0.091** | 0.070 | (1.68) | 0.075 | 0.071 | 0.052 | (0.74) | 0.083 | 0.067 | 0.064 | (0.74) | 2.67 | 2.58 | 2.43 | (0.74) | 1.25 | 2.05 |
| **R&D Dummy** | 0.005 | 0.012 | 0.009 | (0.32) | 0.005 | 0.012 | 0.009 | (0.32) | 0.005 | 0.013 | 0.009 | (0.32) | 0.041 | 0.037 | 0.041* | (0.32) | -0.020 | -0.012 | -0.024 | (0.32) | 0.040** | 0.040*** |
| **R&D_Oil** | 0.011 | 0.001 | 0.021 | (0.10) | 0.011 | 0.001 | 0.021 | (0.10) | -0.084 | -0.204 | 0.003 | (0.10) | -0.071 | -0.004 | 0.048 | (0.10) | 0.266*** | 0.247*** | 0.241*** | -0.065 | 0.008 | 0.039 |
| **IND_MED** | 0.146** | 0.133* | 0.23 | (1.86) | 0.146** | 0.133* | 0.23 | (1.86) | 0.119 | 0.076 | 0.073 | (0.86) | 0.165* | 0.080 | 0.088 | (0.86) | -0.093 | -0.064 | -0.115 | (0.86) | 0.274*** | 0.108 | 0.121* |

This table provides results from the estimation of the partial adjustment model (of speed of adjustment) based on different estimation methods. Columns 1, 4, 7, 10 and 13 reports results of the baseline model (without the oil price variable). Our baseline model is: \( MDR_{it+1} = (1 - \gamma)MDR_{it} + \gamma \delta_{it} + \gamma \delta_{i} + \epsilon_{it} \), and \( \delta_{it} \) is a vector of control variables, such as earnings before interest and tax divided by total asset (EBIT_TA), market-to-book ratio (MB), depreciation scaled by total assets (DEP_TA), size (proxied by the log of total asset), fixed asset proportion (FA_TA), research and development expenses as a proportion of total assets (R&D_TA), dummy variable for unreported R&D expenses (R&D Dummy), and the median industry market debt ratio (IND_MED), and we consider market debt ratio (MDR) as the dependent variable. In the rest of columns the results after inclusion of two oil related variables are reported. GOP_SPOT is the growth rate of spot oil price and D_OIL is the dummy variable, which is equal to 1 when the crude oil price is greater than or equal to $100 and 0 otherwise (oil price psychological variable).

We adopt the panel fixed effects (FE) estimator, the corrected least squares dependent variable (LSDVC) estimator (Bruno, 2005; Kiviet, 1995), the iterative bootstrap-based correction procedure (BC) proposed byEveraert and Pozzi (2007), the long difference (LD) estimator (Hahn et al., 2007), and the generalized method of moments (difference GMM) with initial estimators proposed byArellano and Bond (1991). Standard errors are clustered at the firm level. Finally, ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively.
and volatility is extracted through estimating a GARCH(1,1) model, and call this spot price \((p)\) growth is computed as: \[\frac{p(t) - p(t-1)}{p(t-1)} \times 100.\]

Future/spot price return from futures price growth \((\text{GOP}_\text{FUTURE})\) to open interest growth \((\text{OI}_\text{GROWTH})\) is computed as \[\frac{\text{log} \left( \frac{\text{OI}(t)}{\text{OI}(t-1)} \right) \times 100}{\left( \text{MDR}(t-1) \right)}\] 10% from a one standard deviation increase in these price growths. The economic significance results are presented in Table 5. The abso-

### 4.3. Volume and futures contracts

We also consider other measures of oil market activity, namely, the volume of oil traded and the open interest. The use of volume and open interest constitutes oil market activity because it reflects the number of futures contracts traded while open interest is a measure of liquidity in oil futures market because it represents the number of outstanding futures contracts held by market participants. In other words, as volume of open interest increases, so does market activity and, therefore, liquidity. As Dolatabadi et al. (2017) note, out of all commodities the volume of contracts and outstanding futures contracts are the largest for crude oil. Crude oil makes up appropriately 1/3 of all commodity contracts. The results of the effect of volume and open interest are reported in Panels F and G of Table 6, respectively. We find that the slope coefficient of volume growth is statistically insignificant; the estimated \(t\)-statistic is in the 0.35 to 0.54 range in absolute terms.

The growth rate of open interest, on the other hand, is statistically different from zero in 4/5 estimators. The sign suggests that as liquidity improves it reduces debt, which is just as expected. Liquidity, we find, improves SOA. Across the four estimators where the slope coefficient is statistically different from zero, we see that half-lives falls in the 0.48 to 1.32 years range. This compares to half-lives from the baseline model of 0.54 to 1.69 years range. We conclude that liquidity helps negate asymmetric information in the market thereby contributing to a faster SOA, consistent with Hypothesis 2.

4.4. Economic significance of the role of oil market

We have ascertained that SOA is influenced by oil market activities. To this end, we have shown that not only oil spot price growth matters to SOA, the US$100 psychological barrier and market liquidity also matter to SOA. Even when variables such as the spot/futures price volatilities and oil futures price growth do not strongly influence SOA they appear statistically significantly in the regression model. This evidence, though, is statistical. The goal of this sub-section is to test the economic significance of the role of oil market activities in influencing SOA.

The economic significance results are presented in Table 5. The abso-

This table provides results from the estimation of the partial adjustment model (of speed of adjustment) based on different estimation methods. We adopt the panel fixed effects (FE) estimator, the corrected least squares dependent variable (LSDVC) estimator (Bruno, 2005; Kiviet, 1995), the iterative bootstrap-based correction procedure (BC) proposed by Arellano and Bond (1991). We consider market debt ratio \((\text{MDR}_t)\) to open interest growth \((\text{OI}_\text{GROWTH})\) is computed as \[\frac{\text{log} \left( \frac{\text{OI}(t)}{\text{OI}(t-1)} \right) \times 100}{\left( \text{MDR}(t-1) \right)}\] 10% from a one standard deviation increase in these price growths. Even the volatility of these two prices are meaningful; that is, a one

### 5. Robustness tests

Up to this point, we have tested the robustness of our results on two fronts. First, we have employed a large number of estimators and our results on the SOA and the role of the determinants of leverage remain broadly intact. Second, we have utilized a wide range of control variables in the leverage model. From this analysis, again, our main conclusion that oil market activities influence capital structure holds.
(markable as oil price growth and the psychological barrier effects. Price volatility measures do have an impact but not as re-

Several studies allude to the possibility that the relevance of trade-
off theory is sensitive to the different compositions of stocks, market phases, data sub-samples, firm size, leverage measures, and nonlinear effects. These issues can shape conclusions on SOA and should, thus, not be ignored. We, therefore, investigate the robustness of our conclu-
sions from these perspectives. Specifically, we run the following tests: (1) we use an alternative measure of leverage, namely BDR, to test the effect of oil market activity on leverage and SOA; (2) we categorize stocks into three different sizes to check the sensitivity of SOA to firm size; and (3) we test whether positive and negative rates of growth in oil price influence leverage differently. We are also mindful of the fact that the GFC, because it constituted a major global shock, could also in-
fluence SOA of energy firms. We, therefore, control for the GFC effect as part of robustness tests. Our first robustness test deals with an alternative measure of lever-
age (BDR). We notice that the SOA across the five estimators are broadly similar. The effect of SOA on oil price growth and market liquidity stand out. Price volatility measures do have an impact but not as re-
markable as oil price growth and the psychological barrier effects.

Table 5
Economic significance.

| Variables          | BC            | Difference GMM |
|--------------------|---------------|----------------|
| GOP_SPOT Absolute  | 0.022         | 0.022          |
| % SD               | −9.886        | −9.886         |
| GOP_FUTURE Absolute| 0.024         | 0.019          |
| % SD               | −10.829       | −8.663         |
| VAR_SPOT Absolute  | 0.014         | 0.014          |
| % SD               | 6.361         | 6.231          |
| VAR_FUTURE Absolute| 0.012         | 0.012          |
| % SD               | 5.275         | 5.275          |
| VOL_GROWTH Absolute| 0.000         | −0.003         |
| % SD               | 0.000         | 1.466          |
| OIL_GROWTH Absolute| −0.028        | −0.028         |
| % SD               | −13.045       | −13.045        |
| BASIS Absolute     | 0.001         | 0.002          |
| % SD               | 0.680         | 0.906          |

This table provides results from the economic significance analysis of the importance of oil market variables. The statistical results obtained on the slope coefficient relating to each oil market variable from the iterative bootstrap-based correction procedure (BC) and the difference generalized method of moments (GMM) methods are used to estimate economic significance. We report the absolute value of the effect, which is the slope coeffi-
cient multiplied by the standard deviation, and the effect on leverage from a one standard deviation increase in the oil market activity variable (% SD).

We ideally would like to sub-sample our data and re-run estimation models. However, when we do this split, because our sample is small (1988 to 2015) sub-sampling weakens our sample and in fact given the unbalanced nature of the dataset some of the estimators do not work parsimoniously. We, therefore, do not engage in a sub-sampling exercise.

We turn now to investigating nonlinear effects because oil prices are shown to exert a nonlinear effect on stock prices (Narayan and Sharma, 2011). Motivated by this evidence, we test the sensitivity of leverage (MDR) to positive and negative changes in oil prices. To test this hypoth-

Table 6
Nonlinear effects of oil price on leverage.

| Type of effect | Statistics | FF | LSDVC | BC | LD | Difference GMM |
|----------------|------------|----|-------|----|----|----------------|
| Positive growth | 1 − γ | 0.506 | 0.68 | 0.713 | 0.522 | −0.23 |
| SOA (%)         | 0.494 | 0.32 | 0.287 | 0.478 | N/A |
| half-life (years) | 1.018 | 1.797 | 2.049 | 1.066 | N/A |
| Coefficient     | −0.0010*** | −0.0011*** | −0.0010*** | −0.0012** | −0.0009*** |
| (−3.88)         | (−3.70) | (−2.84) | (−2.26) | (−3.64) | |
| Absolute value  | −0.024 | −0.027 | −0.024 | −0.029 | −0.022 |
| % SD            | −11.10 | −12.21 | −11.10 | −13.32 | 9.99 |
| Negative growth | 1 − γ | 0.097 | 0.29 | 0.29 | 0.452 | 0.689 |
| SOA (%)         | 0.097 | 0.671 | 0.710 | 0.548 | 0.331 |
| half-life (years) | 0.097 | 1.737 | 2.024 | 1.152 | 0.627 |
| Coefficient     | −0.0014*** | −0.0015*** | −0.0014*** | −0.0010*** | −0.0013*** |
| (−4.89)         | (−5.40) | (−4.71) | (−2.74) | (−5.00) | |
| Absolute value  | −0.034 | −0.036 | −0.034 | −0.024 | −0.031 |
| % SD            | −15.53 | −16.64 | −15.53 | −11.10 | −14.42 |

This table provides results for the effect of positive and negative oil spot price growth rate on leverage. We adopt the panel fixed effects (FE) estimator, the corrected least squares depend-

ent variable (LSVEC) estimator (Brunn, 2005; Kiviet, 1995), the iterative bootstrap-based correction procedure (BC) proposed by Everaert and Pozzi (2007), the long difference (LD) esti-
mator (Hahn et al., 2007), and the generalized method of moments (difference GMM) with initial estimators proposed by Arellano and Bond (1991). We consider market debt ratio (MDR) as the dependent variable. Our considered models are MDRit=1 = (1 − γ)MDRit + γiδXit + δ GOPit + POSit + γαit + εit−1 and MDRit=1 = (1 − γ)MDRit + γiδXit + γiδXit + (1 − POSit) + γαit + εit−1. We set POS = 1 when the spot price growth rate is positive and POS = 0 when it is negative. We report the SOA, the half-life, the slope coefficient, δ, the absolute value of the effect (slope coefficient multiplied by the standard deviation), and the effect on leverage from a one standard deviation increase in the oil spot price change (% SD). Standard errors are clustered at the firm level. Finally, *** denotes statistical significance at the 1% level.
activity variable used in tests for SOA, the role of GFC is statistically significant but does not influence the SOA. We, therefore, conclude that our results are insensitive to the GFC.

To conclude robustness testing, we control for macroeconomic variables in our regression model. Hackbart et al. (2006) argue that firms should adjust their policy decisions to business cycle phases. Following Korajczyk and Levy (2003), we utilize three macro variables, namely, terms spread (the difference between US long term government bond and the T-bill rate), the Treasury bill rate (which we proxy using the US 3-month T-bill rate), and the 3-month equity market return for each country in our sample. We find that macroeconomic variables are generally less debt influential. Only the T-bill rate and market returns appear statistically significantly; however, the margin of significant is weak at 10% level in most cases. Overall, their presence does not affect the SOA; detailed results are available upon request.

6. Additional results

This section has two goals. First, to test how corporate debt of non-energy firms responds to oil market activities. This is important because while the aim of this paper is to examine energy firms and how their corporate debt responds to oil market activities, there is no empirical evidence on the responsiveness of non-energy firms to oil market activities. This analysis when done on a global scale involving non-energy firms will provide a direct comparative evidence on the role of oil market activities for corporate debt. We begin by explaining our data sample. The time period and source of data are the same as for the energy firm sample; see Section 3. However, the number of firms, as expected, is much larger; we have 32,382 non-energy firms for which sufficient data are available over the period 1988 to 2015. These firms belong to 108 countries and together we end up with 299,263 firm-year observations. The results on SOA are reported in Table 7. Like in previous tables, the baseline model is estimated without including any of the oil market variables. The panels that follow report in turn augmented versions of the baseline model. The main conclusion from reading results in Table 10 is that the SOA reported from the baseline model is very close to those reported when the baseline model is augmented with the oil market activity variables. This implies that for non-energy firms, oil market activities do not influence SOA. Overall, therefore, this result confirms our main contribution that oil market activities only matter to SOA to leverage of energy firms.

The second goal is to control for country effects in the panel. There are two ways this could be done. One way is to directly control for country effects in the full sample model using dummy variables. We do this and results are available upon request. When we do this, we find slightly stronger effects on SOA but not sufficient to change the conclusion. The second way to deal with this is to split the sample into country panels. The disadvantage of this approach is that the majority of the countries in our panel are too small to warrant specific panel treatment. We do perform separate country panels for six countries and find that the pattern of oil market activities influencing leverage still exists but the results are not robust across estimators. One reason could be that some of the estimators require large sample sizes for it to function parsimoniously. One cost, therefore, of country panel analysis is reduced sample sizes. We, therefore, do not consider these results in our analysis.

Table 7

Regression results from oil market activity variables for global non-energy firms.

| Base model | OIL VARIABLE | With inclusion of OI | With inclusion of OI_FUTURE | With inclusion of VAR_SPOT | With inclusion of VOL_GROWTH | With inclusion of OI_GROWTH |
|------------|--------------|----------------------|----------------------------|-----------------------------|----------------------------|-----------------------------|
| 0.662***   | 0.662***     | 0.662***             | 0.663***                   | 0.663***                    | 0.663***                   | 0.663***                    |
| (129.14)   | (129.29)     | (129.14)             | (129.29)                   | (129.13)                    | (129.18)                   | (129.18)                    |
| Dummy energy firm | -          | -                    | -                          | -                           | -                          | -                           |
| EBIT_TA    | -0.0008      | -0.0001              | -0.0001                    | -0.0004                     | 0.049**                    | 0.051***                    |
| (0.76)     | (0.74)       | (0.76)               | (0.75)                     | (0.77)                      | (0.80)                     | (0.79)                      |
| MB         | 0.000***     | 0.000***             | 0.000***                   | 0.000***                    | 0.000***                   | 0.000***                    |
| (3.11)     | (2.98)       | (2.98)               | (3.09)                     | (3.03)                      | (3.03)                     | (3.12)                      |
| DEP_TA     | -0.010       | -0.010               | -0.010                     | -0.010                      | -0.010                     | -0.010                      |
| (1.43)     | (1.41)       | (1.41)               | (1.41)                     | (1.44)                      | (1.44)                     | (1.43)                      |
| Size       | 0.001        | 0.001                | 0.001                      | 0.001                       | 0.001                      | 0.001                       |
| (0.63)     | (0.61)       | (0.61)               | (0.61)                     | (0.61)                      | (0.61)                     | (0.61)                      |
| FA_TA      | 0.006***     | -0.005***            | 0.006***                   | 0.006***                    | 0.006***                   | 0.006***                    |
| (6.58)     | (6.42)       | (6.42)               | (6.42)                     | (6.42)                      | (6.42)                     | (6.42)                      |
| Red Dummy  | -0.018**     | -0.018**             | -0.018**                   | -0.018**                    | -0.018**                   | -0.018**                    |
| (6.13)     | (6.07)       | (6.07)               | (6.08)                     | (6.08)                      | (6.08)                     | (6.08)                      |
| Red_TA     | -0.005***    | -0.006***            | -0.006***                  | -0.006***                   | -0.006***                  | -0.006***                   |
| (3.40)     | (3.40)       | (3.40)               | (3.40)                     | (3.40)                      | (3.40)                     | (3.40)                      |
| IND_MED    | 0.016**      | 0.016**              | 0.016**                    | 0.016**                     | 0.016**                    | 0.016**                     |
| (2.54)     | (2.54)       | (2.54)               | (2.54)                     | (2.54)                      | (2.54)                     | (2.54)                      |
| SOA (%)    | 0.338        | 0.338                | 0.338                      | 0.337                       | 0.337                      | 0.337                       |
| Half-life (year) | 1.680 | 1.686 | 1.680 | 1.686 | 1.686 | 1.686 |

This table provides results from the estimation of the partial adjustment model (of speed of adjustment) based on the generalized method of moments (difference GMM) with initial estimators proposed by the Arellano and Bond (1991) method. The dataset include all energy and non-energy firms for those countries with energy firms. We consider market debt ratio (MDR) as the dependent variable. Our base model is: MDRfi,t = (1 - \(1 - \gamma\))MDRfi,t-1 + \(\gamma\)Xfi,t-1 + efi,t-1. We augment the base model with interaction of a dummy variable (DUMMYenergy – firm) which takes 1 when we have energy firm and 0 for non-energy firms with each of oil market proxy, from spot price growth (OIL) to open interest growth (OILGROWTH). Future/spot price (p) growth is computed as: \([p(t) - p(t-1)]/p(t-1)\)*100. Future/spot price return volatility is extracted through estimating a GARCH(1,1) model, and we call this VAR SPOT and VAR FUTURE representing spot price return volatility and futures price return volatility, respectively. Volume growth (VOLGROWTH) is computed as log [vol(t)/vol(t-1)]*100, where vol is volume. Open interest growth (OILGROWTH) is computed as log [OI(t)/OI(t-1)]*100, where OI is open interest. In addition, D_OIL represents the oil price psychological barrier effect: it is a dummy variable which takes a value 1 in the year in which the crude oil price is at least US$100 and a value of 0 otherwise. BASIS as the difference between spot and futures prices. In each panel, we report the slope coefficient associated with 1 - \(\gamma\), the SOA which is the \(\gamma\), and the half-life statistic, which is computed as log(0.5)/log(1 - \(\gamma\)). Standard errors are clustered at the firm level. Finally, \*, **, and *** denote statistical significance at 1%, 5% and 10%, respectively.
7. Concluding remarks

This paper uses a unique firm level data on corporate debt to study whether global energy firms’ (756 firms from 56 countries, covering the period 1988 to 2015) leverage decisions are influenced by oil market activities. We proxy oil market activities with spot/futures oil price growth, their volatilities, the US$100 oil price psychological barrier, price basis, volume of contracts traded and open interest (liquidity). We design two hypotheses that have roots in the idea that the oil market is characterized by informational asymmetry (or lack of), which would either delay or improve SOA to leverage. We find both statistical and economic evidence supporting the role of oil market activities in firm leverage. Using oil price growth and the US$100 psychological barrier, we find SOA to leverage is slower for energy firms. The SOA for energy firms when not exposed to these prices is in the range of 33.6–72.5%, culminating into half-lives of between 0.54 and 1.69 years. However, when exposed to these two oil market activity variables, the corresponding half-lives are between 1.03 and 2.15 years. We also find that market liquidity influences SOA. We find that a one standard deviation increase in liquidity has the most (magnitude-wise) effect on leverage. It reduces leverage by 13% of mean leverage. The key implication of our findings is that an oil market activity-augmented trade-off theory model of the determinants of debt offers a better representation of the determinants of capital structure for global energy firms. However, for non-energy firms, the activities in the oil market have no bearing on their corporate debt.

Energy companies will benefit from our findings in the following ways. Liquidity in the energy market is key to reducing financial stress. Liquidity reduces debt. The challenges faced by COVID-19, which saw oil prices record very high volatility and even negative oil prices in April 2020, is likely to exert liquidity pressures (Devpura and Narayan, 2020; Narayan, 2020). From a debt point of view, this is not good news in managing debt. Similarly, oil prices because they matter for firm returns (from their investments) matter to the speed of adjustment to leverage. What we have witnessed in the COVID-19 pandemic phase, globally economic activity has been negatively affected and oil prices are at record lows (Ilyke, 2020a; Huang and Zheng, 2020; Prabheesh et al. 2020). This will impact investment returns for oil companies. Oil related investments will be greatly impacted (see Shen et al. 2020; Qin et al. 2020; Xiong et al. 2020; He et al. 2020). These are likely to have serious repercussions on oil companies’ debt management.

Author statement

Paresh Kumar Narayan: Investigation, methodology, writing first draft, rewriting & editing, methodology.
Maryam Nasiri: Empirical analysis, writing, re-writing, data, methodology, data.

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Appendix A. A plot of market activity variables and descriptive statistics

This figure plots time-series data on the growth rate of oil price (GOP_SPOT), growth rate of futures price (GOP_FUTURE), growth rate of open interest (OI_GROWTH), variance of futures price returns (VARIANCE_FUTURE), variance of spot price returns (VARIANCE_SPOT), growth rate of trading volume (VOL_GROWTH), and basis (BASIS). The plot covers the period 1988 to 2015.
Table A1
Descriptive statistics for oil market activity variables.

| Variables                  | 2   | 3   | 4   | 5   | 6   |
|----------------------------|-----|-----|-----|-----|-----|
| Mean                       | SD  | AR(1) coefficient (t-stat.) | Unconditional correlation (t-stat.) | ADF Unit root test (t-stat.) |
| Oil spot price growth      | GOP_SPOT | 6.328 | 26.245 | 0.123 (0.637) | −0.105 (−8.348) | −0.877 (−4.523) |
| Oil future price growth    | GOP_FUTURE | 4.659 | 23.607 | −0.018 (−0.092) | −0.098 (−7.617) | −1.018 (−5.153) |
| Variance of spot price     | VAR_SPOT | 0.881 | 0.283 | 0.009 (0.052) | 0.051 (3.896) | −0.991 (−5.470) |
| Variance of future price   | VAR_FUTURE | 0.765 | 0.250 | 0.014 (0.080) | 0.046 (3.521) | −0.985 (−5.413) |
| Difference between spot and future price | BASIS | −0.028 | 0.494 | 0.425 (2.391) | −0.007 (−0.526) | −0.575 (−3.233) |
| Open interest growth       | OI_GROWTH | 16.678 | 28.439 | 0.402 (4.382) | −0.066 (−5.066) | −0.598 (−6.513) |
| Volume growth              | VOL_GROWTH | 18.727 | 31.951 | 0.384 (3.538) | −0.022 (−1.718) | −0.616 (−5.665) |

This table presents descriptive statistics for each of the seven oil market activity variables for the time period 1988–2015. Each variable is described in column 1. Mean and standard deviation (SD) appear in columns 2 and 3, respectively. The first order autoregressive (AR(1)) coefficient together with the t-statistic testing the null hypothesis that the coefficient is zero is reported in parenthesis. Column 5 reports unconditional correlation between the market activity variable and the stock return and in parenthesis the t-statistic examining the null hypothesis that the correlation is zero is reported. The last column reports results from a unit root test based on the augmented Dickey-Fuller (ADF) model, which includes a constant term but no trend and the optimal lag length to control for serial correlation is selected using the Schwarz Information Criterion. The t-statistic testing the null of a unit root is reported in parenthesis in column 6.

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