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Are oil price shocks priced in the cross-section of stock returns?

Leonardo Iania[*] Liana Nersisyan[†] P. Thao Nguyen[‡]
Kristien Smedts[§]

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Abstract

This paper investigates whether oil price shocks are priced in the cross-section of U.S. stock returns. We consider a wide range of oil-related measures, covering different sources: structural oil demand and supply shocks, oil price innovations, uncertainty measure surrounding future oil prices, and oil-related news surprises. We further distinguish between positive and negative shock realizations to assess whether the pricing of oil risk depends on the direction of the underlying shock. We find substantial heterogeneity in the pricing of oil related risks. Oil demand and oil price expectation shocks carry negative risk premia for both positive and negative realizations, while supply shocks are not systematically priced. Oil forecast disagreement carries a negative unconditional risk premium, in contrast to the positive risk premium associated with exposure to precautionary inventory shocks. Overall, the cross-sectional pricing of oil exposure depends on the economic source of the shock and, for some sources, on its direction.

Keywords: *Oil price shocks; Cross section stock returns; Oil price uncertainty*

[*]CORE/LIDAM, Université catholique de Louvain, Voie du Roman Pays 34, B-1348 Louvain-la-Neuve, Belgium & KU Leuven, Department Accounting, Finance and Insurance, Naamsestraat 69, 3001, Leuven, Belgium. E-mail address: leonardo.iania@uclouvain.be

[†]CORE/LIDAM, Université catholique de Louvain, Voie du Roman Pays 34, B-1348 Louvain-la-Neuve, Belgium. E-mail address: liana.nersisyan@uclouvain.be

[‡]Corresponding author. KU Leuven, Department Accounting, Finance and Insurance, Naamsestraat 69, 3001, Leuven, Belgium. E-mail address: phuongthao.nguyen@kuleuven.be

[§]KU Leuven, Department Accounting, Finance and Insurance, Naamsestraat 69, 3001, Leuven, Belgium. E-mail address: kristien.smedts@kuleuven.be

1 Introduction

The importance of oil markets in shaping the world economy has become increasingly evident over the past decade. The collapse in oil demand and the episode of negative crude oil futures prices during the COVID-19 pandemic, the surge in energy prices following Russia's invasion of Ukraine, repeated OPEC+ production adjustments, and renewed geopolitical tensions in the Middle East have all highlighted the role of energy markets as a source of global macroeconomic risk. These episodes illustrate that developments in oil markets continue to have broad consequences for economic activity and financial markets.

A large literature documents that oil market disruptions affect inflation, output, unemployment, and monetary policy, with important implications for the business cycle (Hamilton (1983), Cologni and Manera (2008), Hamilton (2009), Kandemir Kocaaslan (2019), Azad and Serletis (2022)). Oil shocks also influence financial markets through their effects on firms' expected cash flows, production costs, discount rates, and investors' expectations (Sadorsky (1999), Park and Ratti (2008), Azimli (2020)).

An important insight from this literature is that oil price movements do not all reflect the same economic forces. For example, higher oil prices may result from stronger global demand, disruptions to oil supply, or increased precautionary demand driven by expectations of future shortages. Although these shocks all raise oil prices, they have very different implications for overall macroeconomic activity. This recognition has led to a growing literature that decomposes oil price movements into structural shocks (Kilian and Park (2009), Baumeister and Hamilton (2019)) , including oil supply shocks, global demand shocks, oil-specific demand shocks, precautionary demand shocks, and more recently, expectation- and uncertainty-driven shocks (Baumeister (2023), Känzig (2021), Iania et al. (2025)). This distinction also matters for financial markets. Equity returns and the term structure of interest rates have both been shown to respond differently depending on the source of the oil shock (Park and Ratti (2008), Ioannidis and Ka (2018), Clements et al. (2019), Iania et al. (2024)).

However, most of the current research focuses on the response of aggregate financial markets to oil market shocks. Much less is known about whether exposure to different structural oil shocks is priced in the cross-section of stock returns. Firms differ substantially in their dependence on energy inputs, production technologies, exposure to global demand, and sensitivity to macroeconomic risks. As a result, oil market developments are unlikely to affect all firms equally. From an asset pricing perspective, if different structural oil shocks capture distinct dimensions of systematic risk, stocks with greater exposure to these risks should earn different expected returns (Merton, 1973). Consequently, understanding how oil-related shocks are transmitted across firms is important for explaining the cross-section of stock returns.

This paper investigates whether exposure to structural oil shocks is priced in the cross-section of U.S. stock returns. We consider a broad set of oil-related risk factors, including conventional structural shocks associated with oil supply, oil-specific demand, and precautionary inventory demand, together with measures that capture innovations in oil prices, expectations of future oil prices, market sentiment, and disagreement among market participants. Using portfolio sorts, Fama-MacBeth cross-sectional regressions, and long-short portfolio strategies, we examine whether different dimensions of oil market risk are reflected in cross-sectional expected stock returns. We further extend our analysis by distinguishing between positive and negative realizations of each oil shock to assess whether investors price favorable and adverse oil market news asymmetrically.

Our results show that the pricing of oil-related risks in the cross-section of stock returns depends importantly on the economic source and the direction of the shock. First, structural oil supply shocks do not command a systematic risk premium in the post-1986 cross-section of stock returns. In contrast, aggregate oil demand shocks and oil price expectation shocks are priced consistently, carrying negative risk premia across both positive and negative realizations. In particular, firms with greater exposure to oil demand and oil price expectation shocks earn lower subsequent returns, and this relation is remarkably similar for positive and negative shocks. The sign-symmetric pattern further indicates that investors value exposure to demand and expectation shocks as a hedge against macroeconomic fluctuations, regardless of shock direction.

The evidence is more nuanced for precautionary demand and oil forecast disagreement. Both inventory shocks and oil forecast disagreement generate significant unconditional return spreads, but these relations largely disappear when the shocks are separated by sign. For inventory shocks, the unconditional premium appears to be driven primarily by negative inventory-demand realizations. This is consistent with negative inventory shocks capturing deteriorating expectations about future economic activity. In contrast, oil forecast disagreement carries a negative risk premium, suggesting that investors value exposure to firms that hedge against greater uncertainty about future oil prices.

Overall, our findings are broadly consistent with the intertemporal asset pricing model of Merton (1973). Oil shocks associated with deteriorating investment opportunities command negative risk premia because they provide valuable hedges against adverse shifts in the investment opportunity set, whereas procyclical oil shocks linked to economic activity command positive risk premia. More generally, our results suggest that investors price the distinct macroeconomic risks embedded in structural oil shocks rather than changes in oil prices alone.

Our paper contributes to the literature on oil market risk and cross-sectional asset pricing in three main ways.

First, we study oil-related risk at the firm level rather than at the level of aggregate stock market indices, industry portfolios, or other broad financial variables like much of the existing literature. This approach captures the considerable cross-sectional heterogeneity in firms' exposure to oil market risk and provides new evidence on how structural shocks are priced on firm-level that may otherwise get lost in aggregate analyses.

Second, we provide a comprehensive analysis of how different dimensions of oil market risk are priced in the cross-section of stock returns. Existing studies typically focus on a single measure of oil shocks, which may paint an incomplete picture of how oil-related risks are priced, as different oil shocks have different economic drivers and are transmitted to financial markets through different channels. By jointly examining structural oil supply, oil demand, and precautionary inventory demand shocks alongside market-based measures of oil price innovations, oil price expectations, and oil market uncertainty, we identify which sources of oil market risk are priced by investors.

Finally, we contribute to the growing literature on asymmetries in asset pricing by showing that the direction of an oil shock is an important aspect of its cross-sectional pricing with its economic origin. While previous studies generally analyze aggregate oil price changes or individual structural shocks, we distinguish between positive and negative realizations of each oil shock. This allows us to examine whether favorable and adverse oil market news are priced differently and to document an important source of asymmetry in the cross-sectional pricing of oil market risk.

The remainder of the paper is organized as follows. Section2 presents the literature review, while Section 3 describes the data and variables used in our study. Section 4 outlines the methodology. Section 5 presents the main results and discusses their economic interpretation, followed by Section 6, which examines the economic drivers of oil risk pricing. Finally, Section 7 concludes.

2 Literature review

A central question in empirical finance is whether macroeconomic shocks represent priced sources of systematic risk. Early literature establishes that macroeconomic factors such as inflation, industrial production, and interest rates have substantial impact on stock returns by altering future cash flows and discount rates (Fama, 1981; Chen et al., 1986). Among these systematic risks, oil price fluctuations have drawn particular attention due to their broad implications on production costs, inflation, consumption, and investment. Hamilton (1983) demonstrates that oil price shocks are closely associated with recessions and economic downturns. Jones and Kaul (1996) show that stock market reactions to oil price shocks can be primarily explained by their impact on expected future cash flows, whereas Bernanke et al. (1997) indicate that oil price shocks also affect inflation and monetary policy. More recently, Kilian and Park (2009) argue that the economic and financial consequences of oil price changes depend critically on the underlying structural source of the shock rather than the oil price movement itself. From an asset pricing perspective, these structural oil market shocks can be formal state variables within the Intertemporal Capital Asset Pricing Model (ICAPM) framework (Merton, 1973).

Because oil shocks shift macroeconomic conditions, they alter future investment opportunities, thus making oil-exposure relevant for intertemporal hedging and providing a strong theoretical rationale for why these exposures command a risk premium.

A key challenge in the oil-market literature concerns the identification and measurement of oil market shocks. Many studies rely on unexpected movements in crude oil prices as a direct proxy for oil-related innovations (Azimli, 2020; Bams et al., 2017). However, identical oil price movements may have fundamentally different economic origins. Consequently, seminar works by Kilian and Park (2009); Hamilton (2009); Baumeister and Hamilton (2019) introduce structural decomposition methods to disentangle the underlying sources of oil price fluctuations into oil supply, aggregate demand, and precautionary demand components. These structurally identified shocks distinguish between physical disruptions in oil production, changes in global economic activity, and shifts in expectations about future oil scarcity. More recently, the literature has increasingly focused on expectations-based measures that capture revisions in market beliefs about future oil prices (Baumeister, 2023; Iania et al., 2025), as well as shifts in investor sentiment surrounding energy markets (Abiad and Qureshi, 2023; Dang et al., 2023). In addition, Känzig (2021) uses high-frequency market reactions to oil-related news announcements to isolate exogenous changes in expectations from broader macroeconomic innovations. Because these alternative measures capture different dimensions of oil market risk, they may have different effects on the cross-section of stock returns.

Building on these measurement developments, a substantial empirical literature has investigated how oil shocks affect stock returns, though the evidence remains mixed. At the aggregate level, several studies find that oil-related risks have limited explanatory power for equity market returns (Henriques and Sadorsky (2008), Apergis and Miller (2009), Azimli (2020)). In contrast, sector-level studies show significant cross-sectional variation, with stronger effects found among oil-producing or heavily exposed sectors like transportation, manufacturing, retail, and tourism (Hedi Arouri and Khuong Nguyen, 2010; Scholtens and Yurtsever, 2012). To better understand these cross-industry dynamics, Broadstock and Filis (2014) further break down the impact of oil price shocks on stock market returns into a direct effect and an indirect effect. The direct effect is the effect of oil price shocks on sector returns. This direct effect is shown to be evident only for certain sectors, but does not hold for all. The indirect effect is the effect of oil price shocks on the aggregate market returns. The authors argue that by impacting the aggregate market returns, oil price shocks also impact individual stock returns via exposure to the market (market beta). The indirect effect is almost always present, with an exception of a structural break during the 2008 Global Financial Crisis.

This variation across sectors and aggregate markets is closely tied to the underlying economic origin of the shock. In their seminar study, Kilian and Park (2009) demonstrate that while physical supply shocks have relatively limited impact on equity markets, positive demand-driven shocks trigger higher stock returns, whereas precautionary demand shocks lower returns by raising macroeconomic uncertainty. More importantly, they find that these oil shocks affect stock prices primarily through changes in expected returns rather than expected dividends. Similarly, Filis et al. (2011) confirm that demand-driven oil shocks strengthen the comovement between oil and stock markets, while supply shocks play only a limited role. Collectively, these findings suggest that both the structural origin of the oil shock and its specific transmission channel are important for understanding the response of equity markets to oil shocks.

However, while this previous literature primarily examines how equity markets respond to oil market shocks, a separate line of asset pricing research addresses a different question: whether investors demand a risk premium for bearing oil-related exposure. Bams et al. (2017) investigate oil price uncertainty using variance risk premia and find that oil uncertainty is largely diversifiable at the aggregate market level, although it remains relevant within oil-sensitive industries. In contrast, Christoffersen and Pan (2018) document a significant cross-sectional premium associated with oil volatility risk in U.S. equities, particularly during periods of heightened financial constraints and economic uncertainty. Expanding on this, Chen and Demirer (2021) show that uncertainty surrounding firms' oil-price exposures itself carries a significant premium in global equity markets, suggesting that investors indeed require compensation for uncertainty about oil-related risk. Similarly, Zhang et al. (2023) finds that Chinese stocks with greater exposure to oil price uncertainty earn lower future returns, with the effect concentrated in manufacturing and transportation industries. Overall, the existing evidence indicates that oil-related risks can be priced in the cross-section of stock returns, although the magnitude and direction of the premium appear to depend on the specific measure of oil risk, the sample period, and the market under consideration[1].

Despite these insights, several important gaps remain in the literature. First, existing studies on oil risk premia typically rely on a single measure of oil shocks, without considering the source of these shocks as well as the channels through which oil-related shocks may impact the equity market. Second, although recent evidence suggests that different types of oil shocks affect financial markets differently, relatively little attention has been paid to potential asymmetries in how equity markets respond to positive and negative oil shocks. Finally, much of the literature focuses on aggregate market indices or broad industry portfolios without further exploring how exposure to oil risk may vary substantially across firms of the same markets and industries.

This paper addresses these gaps by examining the pricing of oil-related risks at firm-level using multiple measures of oil shocks, including price-based, structural,

[1] The stock market effects of oil shocks are likely to differ between oil-importing and oil-exporting economies because oil price increases represent adverse cost shocks for the former but favorable income shocks for the latter (Basher and Sadorsky, 2006; Kilian and Park, 2009; Joo and Park, 2021).

expectations-based, and news-based indicators considering their positive and negative directions. By comparing results across alternative origins of oil shocks and accounting for asymmetries, we provide a more comprehensive assessment of how oil market shocks are priced in the cross-section of stock returns.

3 Data and Variables

This section describes the data and variables used in the empirical analysis. We first introduce the oil-related shock measures employed to capture distinct sources of variation in the oil market. We then describe the firm-level stock data and the variables used in our empirical analysis.

3.1 Oil market variables

We consider four types of measures that capture different dimensions of oil market developments: structure oil shocks, market-based oil price shocks, oil news surprises, and oil price uncertainty.

We begin with the structural oil shocks constructed by Baumeister and Hamilton (2019), which are publicly available from the authors. These comprise the monthly oil supply shock (OSUP), oil-specific demand shock (ODEM), and oil inventory demand shock (OINV). In Baumeister and Hamilton (2019), these shocks are identified using a structural vector autoregression that incorporates oil production, global industrial production, real oil prices, and oil inventories. Oil supply shocks (OSUP) represent unexpected changes in crude oil production as a result of exogenous supply disruptions or expansions, such as geopolitical events or production outages. Oil-specific demand shocks (ODEM) capture unexpected shifts in the demand of oil that are unrelated to contemporaneous global economic activity. Oil inventory shocks (OINV, also referred to as speculative demand shocks) represent unexpected changes in oil inventories, while also accounting for potential measurement error in crude oil inventories.

To capture shocks in oil prices, we employ two oil price expectation measures developed by Baumeister (2023), which are also obtained from the authors' publicly available dataset. The first measure, 1-month oil price surprises (OP1M), is defined as the difference between the realized oil price and the oil futures price one month prior, capturing the total unexpected innovation in oil price from the perspective of market participants. The second measure, pure oil price expectation shocks (OPEX), is obtained by regressing the oil price surprises against oil demand and supply shocks and retaining the residual. OPEX therefore reflects only the changes in beliefs about future oil prices that are not explained by contemporaneous oil market fundamentals. Both the estimated structural oil shocks (Baumeister and Hamilton, 2019) and oil price expectation measures (Baumeister, 2023) are taken directly from the publicly available datasets provided by the original authors rather than being re-estimated in this paper.[2]

As an alternative measure of oil price shocks, we use the oil news surprise measure (ONEW) proposed by Känzig (2021), which we obtain from the author's publicly available replication package. Unlike the structural and expectations-based shocks discussed above, ONEW is a high-frequency measure that captures the immediate response of oil future prices to supply-related news. In Känzig (2021), ONEW is defined as the change in oil future prices relative to the price prior to the news announcement. A positive value therefore represents an unexpected increase in future oil prices following supply-related news. Although ONEW is often interpreted as a supply-related shock, the measure primarily captures price shocks associated with unexpected oil supply news rather than actual oil supply or production shocks. Including ONEW in our analysis allows us to assess whether asset prices respond differently to news-driven changes in oil prices following supply-related announcements than to (i) actual oil supply changes (OSUP) and (ii) broader revisions in expected oil prices inferred from futures markets (OP1M, OPEX).

Finally, to measure uncertainty surrounding future oil prices, we use the Oil Forecast Disagreement (OFD) measure introduced in Iania et al. (2025). OFD captures uncertainty through the cross-sectional dispersion of professional forecasts for future oil prices. Unlike the previous measures which capture realized shocks in oil price expectations, OFD reflects the degree of disagreement among professional forecasters and does not rely on market prices. Greater forecast dispersion therefore indicates higher uncertainty about the future evolution of oil prices. To obtain an innovation measure of OFD, we estimate a rolling AR(1) model over a 36-month window and use the resulting residuals as OFD shocks. We denote this shock measure as OFD-S throughout the rest of the paper. Including OFD-S allows us to examine whether shocks to oil price uncertainty constitute a priced risk factor beyond realized oil-market shocks. Including OFD-S allows us to examine whether oil price uncertainty constitutes a priced source of systematic risk, consistent with the broader asset pricing literature that highlights uncertainty as an important determinant of expected returns beyond realized macroeconomic shocks.

Table 1 presents the pairwise correlations among the oil-related factors described in this section. Most correlations are moderate, suggesting that the different measures capture distinct and complementary aspects of oil market dynamics. The strongest correlation is observed between inventory demand shocks OINV and market-based oil price expectations OP1M (0.76), which is consistent with both measures reflecting expectations about future conditions of the oil market. Similarly, the positive correlation between market-based oil price expectations OP1M and the oil supply news ONEW (0.68) indicates that both respond to similar information regarding future oil price movements. In contrast, oil supply shocks OSUP are negatively correlated with expectation-based measures, particularly market-based oil price expectations OP1M (-0.59) and inventory demand shocks OINV

[2] https://sites.google.com/site/cjsbaumeister/datasets

(-0.48). This highlights the difference between physical supply disruptions and changes in market expectations. Notably, although the oil news surprise measure (ONEW) of Känzig (2021) is derived from OPEC announcements and is often associated with supply shocks, its correlation pattern suggests that it primarily reflects revisions in market expectations rather than physical changes in current oil supply. Overall, the absence of uniformly high correlations across the oil-related factors supports the inclusion of multiple oil-related measures in the empirical analysis, as they capture different aspects of oil market shocks and uncertainty.

Table 1: Pairwise Correlations of Oil-Related Risk Factors

	OSUP	OINV	ODEM	OP1M	OPEX	OFD-S	ONEW
OSUP	1.00	-0.48	0.09	-0.59	0.09	0.06	-0.42
OINV		1.00	-0.36	0.76	-0.11	-0.04	0.68
ODEM			1.00	0.00	0.09	0.01	0.10
OP1M				1.00	0.42	-0.03	0.68
OPEX					1.00	0.04	0.07
OFD-S						1.00	0.09
ONEW							1.00

This table reports Pearson pairwise correlations among the oil-related risk factors. OSUP, ODEM, and OINV are the structural oil supply, oil-specific demand, and oil inventory demand shocks of Baumeister and Hamilton (2019). OP1M is the one-month oil price surprise, OPEX is the orthogonalized oil price expectation shock of Baumeister (2023), OFD-S is innovation of the oil forecast disagreement measure of Iania et al. (2025), and ONEW is the oil news surprise measure of Känzig (2021).

3.2 Stock-level variables

The oil market variables described above are combined with firm-level equity data to examine whether exposure to oil market shocks is reflected in the cross-section of stock returns.

Our empirical analysis is based on all common stocks traded on the NYSE, Amex and Nasdaq exchanges over the period from January 1986 to April 2023. Monthly stock return data are obtained from the CRSP database, while firm-level accounting information is retrieved from the merged CRSP–Compustat database [3]. Following academic convention, we exclude stocks with monthly closing prices below $5 and above $1000 to reduce the influence of illiquid securities and ex-

[3]For common stocks, we filter by share code 10 or 11, and for NYSE, NASDAQ, and AMEX, we filter by exchange codes 1-3 and 31-33.

treme observations. To account for survivorship bias, we adjust delisting returns following Shumway (1997) [4].

We construct a set of firm-specific characteristics for later control experiments, using the CRSP and Compustat databases. These include market beta (β^{MKT}), estimated from rolling regression of stock excess returns against market excess returns; downside market beta ($\beta^{\mathrm{MKT},-}$), estimated from the same rolling regressions but conditional on negative market excess returns; firm size (SIZE), measured as the logarithm of market capitalization; the book-to-market ratio (BM), following Fama and French (1992); operating profitability (OP), calculated as operating income scaled by book equity; short-term reversal (REV), measured as the previous month's stock return (Jegadeesh, 1990); momentum (MOM), measured as cumulative stock returns over the past 12 months excluding the most recent month (Jegadeesh and Titman, 1993); lottery demand (FMAX), calculated as a stock's average of the top five highest returns during the prior month (Bali et al., 2021); idiosyncratic volatility (IVOL), following Ang et al. (2006); illiquidity (ILLIQ), measured according to Amihud (2002); irreversible investment (IRRINV), calculated as net property, plant, and equipment (item PPENT) divided by total assets (AT); and mispricing (MISP), measured using the composite mispricing score of Stambaugh and Yuan (2017).

To control for common sources of systematic risk, we use the standard asset pricing factors commonly employed in the literature. These include the monthly excess market return (MKT), size (SMB), book-to-market value (HML), momentum (UMD), investment (CMA), and profitability (RMW) factors. The factor returns are obtained from Kenneth R. French's data library, where the MKT, SMB, and HML factors are provided following the methodology of Fama and French (1993), the UMD factor follows Carhart (1997), and the CMA and RWM factors correspond to the five-factor model of Hou et al. (2015)[5]. To additionally control for liquidity risk, we include the traded liquidity (LIQ) factor of Ľuboš Pástor and Stambaugh (2003), which is obtained from Lubos Pastor's data library[6]. Finally, individual stock excess returns are calculated by subtracting the one-month U.S. treasury bill rate from monthly stock returns. The Treasury bill rate is obtained from Kenneth R. French's website (originally sourced from Ibbotson Associates).

4 Methodology

To examine whether oil-related shocks represent priced sources of systematic risk, we follow the portfolio construction approach of Fama and French (1993) and the

[4] We set the return to −30% if the delisted code is between 500, 520, 580, 584, 551, and 574 (i.e., the stock was dropped) and to −100% for all other delistings; if the return is not delisted, we use the standard return; if a delisting return is available, it replaces the standard return.

[5] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

[6] https://faculty.chicagobooth.edu/lubos-pastor/data

empirical analysis employed by Bali et al. (2017). The analysis proceeds in several steps.

First, we estimate firm-level exposures to each oil-related shocks using rolling time-series regressions. More formally, for each stock i and month t, we estimate the following rolling time-series regression:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{\mathrm{OIL}}\mathrm{OIL}_t + \sum_{j=1}^{J} \beta_{i,t}^{j} F_{j,t} + \varepsilon_{i,t} \tag{1}$$

where $R_{i,t}$ denotes the excess return of stock i in month t, OIL_t represents one of the oil-related shock measures described in Section 3, and $F_{j.t}$ denotes the return on factor j, where $j \in \{\mathrm{MKT}, \mathrm{SMB}, \mathrm{HML}, \mathrm{UMD}, \mathrm{LIQ}, \mathrm{CMA}, \mathrm{RMW}\}$. The coefficient $\beta_{i,t}^{\mathrm{OIL}}$ captures the sensitivity of stock i's excess returns to the corresponding oil shock, after controlling for exposure to standard equity risk factors $F_{j.t}$. The regression is estimated over a 60-month rolling window, allowing for oil shock exposures to vary over time. To ensure reliable parameter estimates, we require at least 24 monthly return observations within each estimation window.

Second, we examine the relationship between oil shock exposure and future stock returns using portfolio sorts. Each month, stocks are ranked according to their estimated oil shock betas obtained in the first step and assigned to ten decile portfolios. Portfolio returns are computed on an equal-weighted basis and held for one month before the portfolios are rebalanced again using the updated beta estimates. We examine the next-month excess returns and factor-adjusted alphas of the decile portfolios as well as the return spread between the highest- and lowest-beta portfolios.

Given that the economic effects of oil shocks may depend on their direction, we also consider an asymmetric specification that allows firms' exposure to positive and negative oil shocks to differ. This approach is motivated by the broader macroeconomic literature documenting that the sign of oil shock is also economically important and that the effects of oil shocks depend on their direction. Particularly, positive and negative oil shocks affect firms through different transmission channels with different magnitudes, owing to factors such as monetary policy responses (Bernanke et al., 1997) and and irreversible investment (Kilian and Vigfusson, 2011), among others. We therefore estimate:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{\mathrm{OIL},+}\mathrm{OIL}_t^{+} + \beta_{i,t}^{\mathrm{OIL},-}\mathrm{OIL}_t^{-} + \sum_{j=1}^{J} \beta_{i,t}^{j} F_{j,t} + \varepsilon_{i,t} \tag{2}$$

where $\mathrm{OIL}_t^{+} = \max(\mathrm{OIL}_t, 0)$ and $\mathrm{OIL}_t^{-} = |\min(\mathrm{OIL}_t, 0)|$. The coefficients $\beta_{i,t}^{\mathrm{OIL},+}$ and $\beta_{i,t}^{\mathrm{OIL},-}$ measure the sensitivity of stock returns to positive and negative shocks, respectively.

Finally, we complement the portfolio-level analysis with the two-step procedure of Fama and French (1993). Specifically, we run monthly cross-sectional regressions of future excess returns on estimated oil shock betas and the estimated factor betas obtained from Equation 1:

$$R_{i,t+1} = \alpha_t + \lambda_t^{\mathrm{OIL}} \hat{\beta}_{i,t}^{\mathrm{OIL}} + \sum_{k=1}^{K} \gamma_t^k Z_{i,t}^k + \varepsilon_{i,t+1} \tag{3}$$

To examine potential asymmetries in the pricing of oil risk, we additionally estimate an extended specification that allows the price of oil risk to differ between positive and negative shock realizations:

$$R_{i,t+1} = \alpha_t + \lambda_t^{\mathrm{OIL},+} \hat{\beta}_{i,t}^{\mathrm{OIL},+} + \lambda_t^{\mathrm{OIL},-} \hat{\beta}_{i,t}^{\mathrm{OIL},-} + \sum_{k=1}^{K} \gamma_t^k Z_{i,t}^k + \varepsilon_{i,t+1} \tag{4}$$

where $R_{i,t+1}$ denotes the realized excess return of stock i in month $t+1$, $\hat{\beta}_{i,t}^{\mathrm{OIL}}$ is the estimated exposure to the full-sample of oil shock, $\hat{\beta}_{i,t}^{\mathrm{OIL},+}$ and $\hat{\beta}_{i,t}^{\mathrm{OIL},-}$ denote the exposures to positive and negative oil shocks, respectively, and $Z_{i,t}^k$ represents the set of firm-level characteristics, including market beta (β^{MKT}), downside market beta ($\beta^{\mathrm{MKT},-}$), size (SIZE), book-to-market ratio (BM), operating profitability (OP), short-term reversal (REV), momentum (MOM), lottery demand (FMAX), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), irreversible investment (IRRINV), and mispricing (MISP). The cross-sectional regression is performed separately for each month.

The coefficient λ_t^{OIL} represents the monthly price of full-sample oil risk. In the asymmetric specification, $\lambda_t^{\mathrm{OIL},+}$ and $\lambda_t^{\mathrm{OIL},-}$ capture the conditional price of oil risk associated with positive and negative shock realizations, respectively, while γ_t^k captures the effect of the k-th firm characteristic. The average oil risk premium is then obtained as the time-series average of the monthly estimates:

$$\overline{\lambda}^{\mathrm{OIL},s} = \frac{1}{T} \sum_{t=1}^{T} \hat{\lambda}_t^{\mathrm{OIL},s}, \tag{5}$$

where $s \in \{\mathrm{full}, +, -\}$

5 Empirical Results

This section presents our main empirical results on the cross-sectional pricing of oil-related risk. First, we present the univariate portfolio sorts to examine the relationship between firms' exposure to oil-related risks and their risk-adjusted stock returns. Second, motivated by the patterns in the unconditional analysis, we examine asymmetry by distinguishing between positive and negative shock realizations. Finally, we present Fama–MacBeth cross-sectional regressions for both the unconditional and conditional analyses.

5.1 Univariate portfolio analysis

We examine whether oil shock exposure is associated with differences in risk-adjusted portfolio returns. Following the procedure described in Section 4, stocks are sorted each month into equal-weighted decile portfolios based on their estimated oil shock betas. Table 2 reports the resulting portfolio factor-adjusted returns (alphas) relative to the seven-factor model that controls for market, size, value, liquidity, momentum, investment, and profitability.

Overall, the portfolio sorts provide little evidence of a monotonic relation between oil shock exposure and abnormal returns. Rather than increasing or decreasing steadily with oil beta, portfolio alphas exhibit a pronounced U-shaped pattern for most oil shock measures (see Figure A1). Specifically, both the lowest- and highest-exposure portfolios tend to earn larger abnormal returns than the middle portfolios. For example, portfolios sorted on exposure to the oil supply shock (OSUP) exhibit alphas of 0.42% and 0.45% per month in the lowest- and highest-beta deciles, respectively, while the middle deciles earn substantially lower returns (around 0.20%). A similar pattern can be seen for the market-based oil price expectation measures, OP1M and OPEX, where both extreme portfolios generate comparable alphas (around 0.60%) and the intermediate portfolios earn significantly less (around 0.22%). This non-monotonicity is also reflected in the long-short spreads. The return differences between the highest and lowest decile portfolios (High–Low) are economically small and statistically insignificant for most oil shock measures. This suggests that after controlling for conventional risk factors, firms with extreme positive exposure to oil-related shocks do not systematically outperform or underperform firms with extreme negative exposure.

Two measures stand out from this general pattern: OINV and OFD-S. Unlike the other oil shock measures, these variables generate economically meaningful and statistically significant differences between the extreme portfolios. For OINV, alpha rises from 0.10%–0.14% in the second and third deciles to 0.60% in the highest-exposure decile. The resulting High–Low spread is positive and significant at 0.27% per month (t-statistics = 2.44), indicating that investors demand higher expected returns for holding stocks that are more sensitive to precautionary oil demand shocks. In contrast, OFD-S exhibits a declining return pattern across the deciles: alpha falls from 0.51% in the lowest-exposure portfolio to only 0.15% in the highest-exposure portfolio. The corresponding High–Low spread is negative and significant at 0.36% per month (t-statistic = -2.38). Thus, greater exposure to oil forecast disagreement is associated with lower subsequent risk-adjusted returns. The opposite signs of these two spreads are particularly noteworthy: while greater sensitivity to OINV is associated with higher expected returns, greater sensitivity to OFD-S is associated with lower expected returns. Although both measures are related to uncertainty in oil markets, they capture different economic dimensions

Table 2: Risk-adjusted returns of decile portfolios sorted on oil shocks exposure

Variable	OSUP	ODEM	OINV	OP1M	OPEX	OFD-S	ONEW
Low	0.42	0.55	0.33	0.60	0.57	0.51	0.40
2	0.31	0.33	0.10	0.40	0.34	0.38	0.22
3	0.22	0.27	0.14	0.24	0.24	0.29	0.28
4	0.22	0.23	0.23	0.25	0.22	0.30	0.21
5	0.21	0.25	0.19	0.22	0.20	0.42	0.32
6	0.26	0.26	0.27	0.22	0.32	0.35	0.23
7	0.19	0.18	0.28	0.32	0.26	0.37	0.21
8	0.29	0.22	0.32	0.28	0.37	0.32	0.24
9	0.34	0.21	0.44	0.44	0.50	0.28	0.36
High	0.45	0.40	0.60	0.62	0.58	0.15	0.44
High-Low	0.03	-0.15	**0.27**	0.02	0.00	**-0.36**	0.04
	(0.19)	(-1.45)	(2.44)	(0.14)	(0.03)	(-2.38)	(0.34)

Note: For each oil shock, stocks are sorted each month into ten equal-weighted portfolios based on their estimated oil beta, with the first (Low) and tenth (High) deciles representing firms with the lowest and highest exposures, respectively. The table reports the monthly risk-adjusted returns (alphas) for each portfolio, estimated relative to the seven-factor model comprising the market, size, value, momentum, investment, profitability, and liquidity factors. The bottom row reports the difference in risk-adjusted returns between the highest- and lowest-exposure portfolios (High–Low). Newey-West adjusted t-statistics are reported in parentheses. Bold values indicate statistical significance at the 5% level.

of uncertainty. An increase in OINV may capture exposure to uncertainty about future physical oil production or an anticipation of price increases, whereas an increase in OFD-S reflects heightened disagreement about future oil prices.

These results suggest that the pricing of oil-related risk is not uniform across the different economic sources. In particular, the significant and opposite signed spreads for OINV and OFD-S indicate that the cross-section does not simply reward or penalize firms according to their exposure to oil-related uncertainty. Rather, the direction of the relation appears to depend on the underlying source of the shock. At the same time, the non-monotonic patterns observed for most other measures provide little support for a single linear pricing relation between oil shock exposure and expected returns. This raises the possibility that firms' valuation may respond differently to positive and negative realization of oil shocks. The next subsection therefore separates positive and negative oil shock realizations and examines whether they are associated with different return patterns.

5.2 Asymmetry in oil shock premia

To examine whether the pricing of oil-related risk depends on the direction of the shock, we estimate separate firm-level sensitivities to positive and negative oil shock realizations using Equation 2. This specification avoids pooling shocks of opposite signs, allowing positive and negative oil market developments to represent distinct sources of risk. For ease of interpretation, negative oil shocks are transformed into their absolute values, so that both positive and negative shock exposures are measured on a comparable scale. Table 3 reports the risk-adjusted returns for the High, Low, and High–Low portfolios sorted independently on the estimated positive ($\beta^{\text{OIL},+}$) and negative oil betas ($\beta^{\text{OIL},-}$).

Overall, separating shocks by their direction substantially changes the relation between oil shock exposure and future stock returns. While the unconditional portfolio sorts in Table 2 exhibit a pronounced U-shaped pattern, the directional portfolio sorts reveal that the shock asymmetry differs across oil shock measures. For some shocks, conditioning on the sign alters the price relation clearly, whereas for other shocks it weakens or eliminates the relationship observed in the unconditional specification.

The most notable results concern precautionary demand (OINV) and oil forecast disagreement (OFD). In the unconditional portfolio analysis, both measures already generate statistically significant High–Low spreads, indicating that these sources of oil-related risk are priced even without distinguishing between positive and negative realizations. Once the shocks are separated by sign, however, their behavior differs. For OINV, the positive unconditional High–Low alpha is driven by a significant negative inventory shocks: the High–Low alpha for negative shocks is -0.24% (t-stat -2.01), while the corresponding spread for positive inventory shocks is economically small and statistically insignificant at 0.08% (t-stat 0.64). Thus, the unconditional specification masks important differences between positive and negative inventory shocks. By contrast, decomposing oil forecast disagreement (OFD-S) into positive and negative realizations eliminates the significant pricing relation observed in the unconditional analysis. These results suggest that the unconditional pricing of oil-related uncertainty is sensitive to how the underlying shocks are defined and, in particular, is not robust to separating positive and negative realizations.

A different pattern emerges for oil demand shocks and market-based measures of oil price shocks. For ODEM, OP1M, OPEX, and ONEW, separating positive and negative shocks reveals a remarkably consistent pricing relation. Firms with greater exposure to either positive or negative shocks earn significantly lower abnormal returns than firms with lower exposure. For instance, the High–Low portfolio formed on positive OP1M betas earn an alpha -0.61% per month (t-stat -3.30), while the corresponding portfolio formed on negative OP1M betas earns a similarly large alpha of -0.54% (t-stat -3.10). Comparable results are found for ODEM, with High–Low alphas of -0.56% (t-stat -3.12) and -0.36% (t-stat -2.30) for positive and negative shocks, respectively, and for OPEX, with -0.34%

(-2.07) for positive and -0.39% (t-stat -2.23) for negative shocks. Oil news surprises (ONEW) also generate a significant negative spread for positive shocks (-0.32%, t-stat -2.37), although the negative-shock High–Low portfolio is not statistically significant (-0.27%, t-stat 1.64). Overall, when positive and negative shocks are treated as distinct risk factors, they both command similarly negative risk premia. This indicates that investors value exposure to large oil demand and oil price shocks irrespective of their direction.

Oil supply shocks (OSUP), on the other hand, continue to exhibit little evidence of cross-sectional pricing. Neither the unconditional nor the directional portfolio sorts produce statistically significant return spreads, suggesting that exposure to unexpected oil supply disturbances is not systematically rewarded in expected stock returns.

Taken together, the conditional portfolio analyses demonstrate the importance of conditioning on both the direction of oil shocks as well as on the underlying source of oil market risk. For oil forecast disagreement, the significant negative unconditional return spread disappears once positive and negative shocks are considered separately. Decomposing oil supply shocks also adds little, as neither the unconditional nor the directional portfolio sorts exhibit significant return spreads. However, for precautionary demand shocks, separating positive and negative shocks fundamentally changes the inferred pricing relation. Finally, for oil demand and oil price expectation shocks, directional exposures show systematic cross-sectional differences in abnormal returns that are not evident when positive and negative shocks are pooled together. The next subsection examines whether these conditional shocks reflect priced sources of systematic risk using Fama-Macbeth two-stage procedure.

5.3 Fama-MacBeth regressions

The portfolio analyses presented in the previous subsections indicate that the pricing of oil-related risk depends on the underlying source of the shock and, for several measures, on its direction. We now examine whether these exposures remain priced in the cross section after controlling for a broad set of firm characteristics. Table 4 reports the average monthly risk premia estimated from the Fama-Macbeth cross-sectional regressions. The first row reports the price of risk associated with the full-sample oil shock beta, λ^{OIL}, where exposure is estimated using all oil shock realizations. The subsequent rows report the prices of risk associated with positive and negative oil shock betas, $\lambda^{\mathrm{OIL},+}$ and $\lambda^{\mathrm{OIL},-}$, which enter the cross-sectional regression simultaneously. The estimated coefficients are then averaged over time. To facilitate comparisons across oil shock measures, all oil shocks are standardized prior to the first-stage rolling time-series regressions so that the second stage risk premia are on a comparable scale.

Overall, the Fama-Macbeth estimates broadly reinforce the conclusions from the both unconditional and conditional portfolio analysis. For oil inventory shocks

Table 3: Risk-adjusted returns of decile portfolios sorted on positive and negative oil shocks exposure

	Variable	OSUP	ODEM	OINV	OP1M	OPEX	OFD-S	ONEW
Positive	High	0.27	0.09	0.39	0.19	0.28	0.31	0.19
	Low	0.44	0.65	0.32	0.80	0.63	0.41	0.51
	High-Low	-0.17	**-0.56**	0.08	**-0.61**	**-0.34**	-0.10	**-0.32**
		(-1.22)	(-3.12)	(0.64)	(-3.30)	(-2.07)	(-0.52)	(-2.27)
Negative	High	0.26	0.21	0.24	0.27	0.35	0.37	0.24
	Low	0.41	0.58	0.48	0.81	0.74	0.35	0.52
	High-Low	-0.14	**-0.36**	**-0.24**	**-0.54**	**-0.39**	0.02	-0.27
		(-1.37)	(-2.30)	(-2.01)	(-3.10)	(-2.23)	(0.09)	(-1.64)

Note: For each oil shock, stocks are sorted each month into ten equal-weighted portfolios based on their estimated oil beta, with the first (Low) and tenth (High) deciles representing firms with the lowest and highest exposures, respectively. The table reports the monthly risk-adjusted return (alpha) of the High–Low portfolio, constructed by holding long the highest-beta and short the lowest-beta decile portfolios. Positive (negative) shocks refer to months in which the corresponding oil shock realization is positive (negative). Risk-adjusted returns are estimated relative to the seven-factor model comprising the market, size, value, momentum, investment, profitability, and liquidity factors. The bottom row reports the difference in risk-adjusted returns between the highest- and lowest-exposure portfolios (High–Low). Newey-West adjusted t-statistics are reported in parenthesis. Bold values indicate statistical significance at the 5% level.

and oil forecast disagreement, the unconditional pricing relations do not persist when exposures are decomposed by shock direction. OINV carries a positive unconditional price of risk and OFD-S carries a negative unconditional price of risk, but neither exhibits significant risk premia for positive and negative shock exposures. For oil demand shocks, oil price expectation shocks, and oil price surprises, both positive and negative shock exposures are associated with negative risk premia. Although several estimates fail just below conventional levels of statistical significance, the consistency in their sign across measures and shock directions provides evidence that the cross-sectional pricing of these oil-related risks is not solely driven by differences in firm characteristics.

The strongest evidence of directional pricing is found for aggregate oil demand shocks (ODEM). Both the positive and negative oil demand betas command economically large and statistically, albeit marginally, significant negative prices of risk, with estimated premia of -5.16% (t-stat -1.71) and -5.26% (t-stat -1.72) per month, respectively. These results closely mirror the portfolio-level analysis evidence, which shows that firms with greater exposure to either positive or negative demand shock consistently earned lower abnormal returns. The similarity of the estimated premia (-5.16% versus -5.26%) suggests that investors require similar compensation for exposure to unexpected changes in global oil demand regardless of the direction of the underlying shock.

A comparable pattern can be seen for the market-based oil price measures. Positive and negative exposures to OP1M are both associated with negative premia of -0.12% and -0.15% per month, while OPEX produces smaller but still consistently negative estimates of -0.03% and -0.06%. Likewise, oil news surprises (ONEW) generate negative coefficients for both directional oil betas. Although these estimates are not statistically significant individually, their signs are fully consistent with the previous portfolio analyses, which showed that firms with larger sensitivities to oil price shocks generally earn lower subsequent returns. Taken together, these findings suggest that investors price exposure to unexpected oil price movements and revisions in oil price expectations rather than distinguishing between favorable and unfavorable oil price movements.

On the other hand, oil supply shocks (OSUP) provide little evidence of cross-sectional pricing. Neither the full-sample oil supply beta nor the positive and negative supply shock betas are associated with significant risk premia. This finding, together with the previous portfolio analysis results, shows that exposure to oil supply innovations does not represent a priced source of systematic risk.

The pricing of precautionary demand shocks (OINV) and oil forecast disagreement (OFD-S) differs from that of the other oil shock measures. Both measures retain the pricing patterns observed in the unconditional portfolio analysis: OINV carries a positive price of risk (3.14% per month, t-stat 2.00), and OFD-S carries a negative price of risk (-5.91% per month t-stat -2.11). However, decomposing these shocks into positive and negative realizations eliminates the directional pricing relation, as both positive and negative exposure produces economically small and statistically insignificant coefficients of opposite signs. For OINV, this differs from the conditional portfolio analysis, where negative inventory shocks produced a significant return spread. The lack of significance in the Fama-Macbeth regressions suggests that the portfolio-level OINV results may largely reflect the extreme portfolios rather than a linear pricing relation. Overall, these findings suggest that, unlike oil demand and oil price expectation shocks, the pricing of OINV and OFD-S reflects exposure to the aggregate shock rather than a systematic different response to positive and negative realizations.

Altogether, these results highlight that the pricing of oil-related risk depends on the economic mechanism generating the shocks and that accounting for directional exposures provides additional insights into the cross-section of expected stock returns. For demand and price-based shocks, separating positive and negative realizations confirms that exposure to either direction is associated with lower expected returns. For OINV and OFD-S, the relevant pricing relation is captured by aggregate exposure rather than directional shock exposure. Meanwhile, oil supply shock remains largely unpriced. Thus, the Fama-MacBeth results reinforce the view that oil-related risk is not a homogeneous source of systematic risk.

Table 4: Risk premia associated with positive and negative oil shock exposures

Variable	OSUP	ODEM	OINV	OP1M	OPEX	OFD-S	ONEW
λ^{OIL}	-1.37%	0.32%	**3.14%**	2.19%	2.23%	**-5.91%**	1.80%
	(-0.87)	(0.18)	(2.00)	(1.02)	(1.12)	(-2.11)	(0.91)
$\lambda^{\text{OIL},+}$	-1.93%	-5.16%	0.43%	-0.12%	-0.03%	-1.58%	-0.36%
	(-1.80)	(-1.71)	(0.44)	(-1.75)	(-0.86)	(-1.01)	(-0.81)
$\lambda^{\text{OIL},-}$	-0.31%	-5.26%	-0.53%	-0.15%	-0.06%	0.69%	-0.81%
	(-0.26)	(-1.72)	(-0.47)	(-1.59)	(-1.50)	(0.65)	(-1.36)

Note: This table presents the average monthly prices of risk estimated using the Fama-Macbeth cross-sectional regression procedure according to Equations 3-5 described in Section 4. Newey-West adjusted t-statistics are reported in parenthesis. Bold values indicate statistical significance at the 5% level.

6 Discussion: The Economic Drivers of Oil Risk pricing

The empirical analyses presented above provide consistent evidence that the cross-sectional pricing of oil-related risk is both nonlinear and asymmetric. Rather than pointing to a single source of risk premium related to oil shocks, our findings imply that the pricing of oil risk is dependent on both the economic source and direction of the shock. Following up on existing theories of asset pricing and oil market dynamics, this section brings together the main findings and discusses the economic mechanisms that can explain the observed patterns.

To provide additional context for the economic interpretation of our findings, we extend our analysis to further explore whether the observed pricing relations coincide with systematic differences in firm characteristics and whether the documented return patterns persist after controlling for these characteristics. The results are reported in Appendix B followed by the results of bivariate portfolio sorts in Appendix C. These supplementary analyses leave the main conclusions unchanged while providing additional economic context for the documented cross-sectional pricing relations. Given the large number of cross-sectional hypothesis tests involved, they are best viewed as exploratory evidence intended to aid the economic interpretation of the main findings rather than as formal tests of the underlying pricing mechanisms.

Three key findings are the focus of our discussion. First, rather of fluctuating monotonically across the cross-section, the U-shaped return patterns seen for the majority of oil shock exposures imply that the pricing of oil-related risk is concentrated among businesses with severe sensitivity. This nonlinearity indicates that a single linear relation between oil exposure and expected returns may not fully capture the cross-sectional pricing of oil risk. Second, economically significant directional asymmetries that are hidden when oil exposures are evaluated unconditionally are revealed by separating positive and negative shock realisations. And finally, the strength and robustness of these pricing patterns differ across the economic sources of oil market fluctuations. We therefore organize the discussion around economically related groups of shocks.

Oil supply shocks. The most surprising finding of our study relates to structural oil supply shocks. Given their significant role in discussions of oil-related macroeconomic risk (Baumeister and Hamilton (2019)), we would expect supply disruptions to matter, yet we find almost no evidence of pricing. One possible explanation is that structural supply shocks have become relatively rare after the mid-1980s. Hamilton (2009) argue that while earlier major oil shocks, especially in the 1970s, were primarily supply-driven, the 2007-08 oil price increase was largely driven by strong demand. More generally, the post-1986 period may therefore contain relatively few large and exogenous supply disruptions. Since our analysis covers the period from 1986 to 2023, the limited incidence of such shocks in the sample could explain why we do not find any evidence of supply shocks being systematically priced in the cross-section of stock returns. In addition, modern oil markets may buffer production disruptions through inventories and spare capacity, further reducing their effects on firms' expected cash flows.

Our finding is consistent with Kilian and Park (2009), who show that unexpected global oil-supply shocks have no statistically significant effect on aggregate U.S. stock returns and are relatively unimportant in explaining stock price variation. At the industry-level analysis, nevertheless, oil supply shocks can have economically meaningful effects on particular industries. Using the structural oil shocks of Baumeister and Hamilton (2019), Huang et al. (2021) finds economically significant responses to oil-supply disturbances at industry level. Our analysis complements this evidence by moving from industry-level responses to the question of systematic cross-sectional pricing. Despite potentially heterogeneous effects across industries, we find little evidence that exposure to structural oil-supply shocks commands a persistent risk premium in the cross-section of stock returns.

Oil demand and oil price shocks. The central finding of the paper concerns the pricing of oil demand and oil price shocks. For global oil demand shocks, oil price surprises, and oil price expectation shocks, we report negative and statistically significant risk premia for both positive and negative realizations. This pattern suggests that the relevant source of risk is not the sign of the shock itself, but rather firms' sensitivity to the broader economic information embedded in demand and oil price shocks.

This perspective is especially relevant for global oil demand shock (Kilian and Park (2009)), which reflect changes in global business cycle, revisions about future economic activity, or other macroeconomic news. Firms with high demand betas may consequently be those whose cash flows fluctuate more with aggregate macroeconomic conditions. The negative risk premia associated with these exposures may therefore be consistent with an intertemporal hedging interpretation: investors are willing to accept lower expected returns for firms who provide payoffs that are valuable when aggregate investment opportunities deteriorate, rather than requiring compensation for exposure to a particular direction of oil-price movements [7].

A similar but distinct channel is suggested by the pricing of oil price surprises and oil price expectation shocks. Oil price surprises capture innovations relative to market participants' prior expectations and therefore incorporate new information about oil market conditions, whereas oil price expectation shocks isolate revisions in beliefs about future oil prices that are not explained by contemporaneous supply and demand fundamentals. Our findings extend the importance of expectations in understanding unexpected oil price movements to the cross-section of stock returns: the negative risk premia associated with both positive and negative realizations suggest that the pricing of oil-related risk appears to go beyond current market fundamentals to include firms' exposure to unforeseen fluctuations in oil prices and changes in expectations regarding future conditions of the oil market (Baumeister and Kilian (2016)).

Oil forecast disagreement shocks. We find that oil forecast disagreement shocks (OFD-S) carry a significant negative risk premium in the unconditional specification, whereas decomposing the shocks into positive and negative realizations eliminates the pricing relation. This is consistent with the broader asset pricing literature documenting a negative premium for macroeconomic uncertainty, such as Bali et al. (2017) and Iania et al. (2025). Although our measure is specific to the oil market, it is conceptually related to the uncertainty innovations of Jurado et al. (2015). From an intertemporal asset-pricing perspective, the negative risk premium may thus reflect a hedging channel if firms with greater exposure to innovations in oil-market disagreement provide relatively valuable payoffs when uncertainty about future economic conditions increases.

Oil inventory (precautionary demand) shocks. Precautionary demand shocks exhibit a distinct pricing pattern. Exposure to inventory demand yields a positive risk premium in the unconditional analysis, indicating that firms who are more sensitive to this source of variation in the oil market require higher expected returns. In the structural framework of Baumeister and Hamilton (2019),

[7] Consistent with this interpretation, exposure to both positive and negative global oil demand shocks is systematically related to market and downside market betas (Appendix B), while the negative risk premia remain significant after controlling for these characteristics in the bivariate portfolio sorts (Appendix C).

inventory shocks capture forward-looking demand for physical oil that is not explained by the other structural oil-market shocks. From an ICAPM perspective, since oil inventories function as a buffer for consumption and production smoothing, inventory accumulation can reflect changes in the future investment opportunity set rather than uncertainty about oil prices or belief dispersions. A possible explanation for the positive risk premium is that investors want compensation for taking on this risk if companies with more inventory-demand exposure perform badly when investment possibilities decline [8].

The sign-specific results further suggest that the pricing relation may be driven primarily by negative inventory-demand realizations. Exposure to negative shocks results in a negative High–Low spread, whereas exposure to positive inventory demand shocks is not considerably priced. This implies that the economic effects of inventory shocks depend on their direction and that the unconditional positive premium does not simply represent a symmetric compensation for inventory-demand risk. Conceptually, a negative inventory demand shock signals a decline in forward-looking precautionary demand, which can arise from either weaker expectations about future economic activity or easing supply constraints. The former appears more relevant in this setting. Under the sign restrictions of Baumeister and Hamilton (2019), an inventory demand shock is structurally identified such that negative realizations explicitly co-move with falling real oil prices and falling inventories, ruling out positive physical supply expansions. This suggests that negative precautionary demand shocks capture pessimistic expectations of future economic activity. Since negative shocks enter the exposure estimation in absolute terms, firms with higher negative inventory-demand betas perform relatively better as adverse inventory-demand shocks become larger. If such shocks reflect deteriorating expectations about future economic activity, these firms offer a hedge against worsening macroeconomic conditions. Investors may therefore be willing to accept lower expected returns for holding them, resulting in the negative risk premium observed in the cross-section. The negative directional risk premium can coexist with a positive unconditional risk premium, because both measures represent economically different aspects of inventory-demand shock.

7 Conclusion

We examine whether exposure to different sources of oil-market risk is priced in the cross-section of stock returns. Using structural oil shocks, we estimate firms' time-varying exposures to oil supply, demand, inventory, price expectation, and forecast disagreement shocks and test whether these exposures predict future

[8]The complementary bivariate analysis reinforces this distinction. The unconditional inventory-demand premium remains positive and statistically significant across all characteristic controls, whereas the spreads associated with negative realizations remain negative, with significant results for investment irreversibility and mispricing (Appendix C)

returns. We also distinguish between positive and negative shock realizations to examine whether the pricing of oil risk depends on the direction of the shock.

Our empirical findings reveal four main insights. First, physical oil supply shocks do not generate a systematic risk premium in the post-1986 cross-section of stock returns. Second, aggregate oil demand and oil price expectation shocks carry negative risk premia for both positive and negative realizations. Third, oil forecast disagreement also carries a negative risk premium, although this relation does not survive the separation of shocks by sign. Fourth, precautionary inventory shocks generate a positive unconditional premium that is driven primarily by negative inventory-demand realizations. Overall, the results show that oil risk is not priced as a single, uniform source of risk. Instead, the pricing relation depends on the underlying economic source of the shock and, for some shocks, on its direction.

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A Additional Portfolio Sort Results

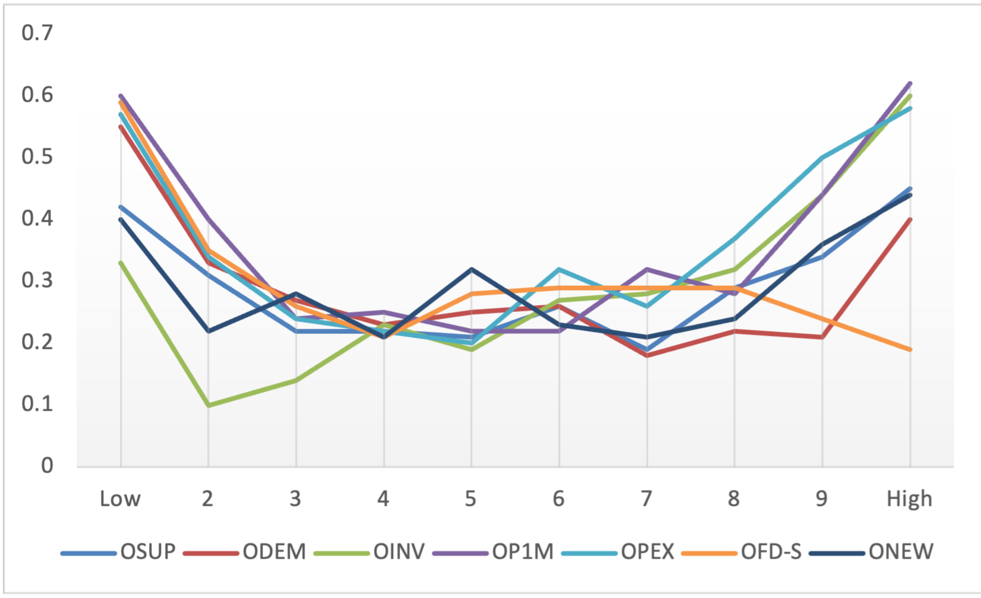

Figure A1: Seven-factor alphas of decile portfolios sorted by oil shock exposure. The figure plots the average monthly abnormal returns (in percent) of decile portfolios formed on estimated oil shock betas. Portfolios are ordered from the lowest (Low) to the highest (High) oil shock exposure. The figure provides a graphical representation of the portfolio alphas reported in Table 2. For most oil shock measures, risk-adjusted returns display a pronounced U-shaped pattern, with both the lowest- and highest-exposure portfolios earning higher abnormal returns than portfolios with intermediate exposures.

B Average stock characteristics

To better understand the cross-sectional pricing results, we examine which firm characteristics are associated with exposure to the different oil shock measures. Following Bali et al. (2017), we regress the estimated positive ($\beta^{\mathrm{OIL},-}$) and negative oil shock betas ($\beta^{\mathrm{OIL},-}$) on the set of firm characteristics used in the Fama-Macbeth analysis. More formally:

$$\beta_{i,t}^{\mathrm{OIL},s} = \lambda_{0,t} + \sum \lambda_{1,t} Z_{i,t} + \epsilon_{i,t}, \quad s \in \{+,-\} \tag{6}$$

where $\beta^{\mathrm{OIL},+}$ and $\beta^{\mathrm{OIL},-}$ are estimated via rolling-window regressions in the first step, and $Z_{i,t}$ is the vector of firm-level control characteristics measured at time t.

Table A1 reports the average slope coefficients from these monthly cross-sectional regressions for positive (Panel A) and negative (Panel B) oil shocks. The estimates describe the types of firms that exhibit greater sensitivity to each source of oil market risk, providing insight into the economic channels underlying the pricing results documented in the previous subsections.

According to our results, several firm characteristics exhibit strikingly consistency relative to both positive and negative oil shocks. In particular, downside market beta ($\beta^{MKT,-}$), the irreversible investment measure (IRRINV), the mispricing measure (MISP), firm size (SIZE), and the book-to-market ratio (BM) are the most significant determinants of oil shocks exposure. Downside market beta is one of the most interesting determinants of directional oil shock exposure. While it has a mixed relationship with positive oil shocks (negative coefficient for ODEM, OP1M and OFD-S and positive for INV), downside market beta is statistically significant and negative for all negative oil shocks. This result suggests that firms with higher downside market risk typically exhibit less sensitivity to negative oil shocks after controlling for other firm characteristics. The outcome highlights that companies sensitive to oil shocks are not just those that perform poorly during widespread market downturns, indicating that oil-related risk captures a dimension of systematic risk that is different from traditional downside market risk. For negative oil shocks there is another interesting significant finding: the two market beta metrics are different for oil shock exposure. For example, for OSUP, ODEM and ONEW market beta is positive while downside beta is negative. This result indicates that firms exposed to oil shocks tend to have high overall systematic risk (positive β^{MKT}), but low downside market sensitivity, which suggests that while oil-sensitive firms are generally more cyclical, they may not always move in tandem with market during bad times.

Next characteristic of the stock that consistently explains directional oil shock exposure is the irreversible investment measure (IRRINV) by Kilian and Vigfusson (2011). The average coefficient on IRRINV is positive and statistically significant for several positive oil shocks (ODEM, OP1M, OPEX, ONEW). In contrast , for negative oil shocks, the relation reverses for most of oil shocks with significantly negative coefficients for (OINV, OP1M, OPEX, OFD-S, ONEW). This asymmetric pattern implies that firms with more investment irreversibility react to advantageous and disadvantageous changes in the oil market in different ways. Firms with higher adjustment costs seem to be more exposed when the oil market improves but less exposed when negative oil shocks occur because they have less flexibility to change their capital stock.

A similar robust pattern is observed for Stambaugh and Yuan (2017) mispricing measure (MISP), which is significant over wide range of oil shocks. Although the sign of the relationship differs across positive and negative oil shock realisations, the results show that businesses with varying oil shock exposures also differ systematically in their degree of relative mispricing, suggesting an asymmetric relationship between oil risk and market mispricing.

Firm size (SIZE) and the book-to-market ratio (BM) also explain a substantial part of the cross-sectional variation in directional oil shock exposures. Firm size exhibits a relatively consistent pattern across specifications. For positive oil shocks, larger firms are significantly more exposed to oil supply (OSUP) and forecast disagreement (OFD-S) shocks, while they exhibit lower exposure to precautionary inventory demand (OINV) shocks. For negative oil shocks, the relation becomes even more pronounced, with positive and significant coefficients for OSUP, OP1M, OPEX, OFD-S, and ONEW, suggesting that larger firms are generally more sensitive to several adverse oil market disturbances. The book-to-market ratio displays similarly robust explanatory power. Across both positive and negative shock realizations, value firms exhibit greater exposure to oil supply (OSUP) shocks and lower exposure to precautionary inventory demand (OINV) shocks. For oil price changes (OP1M), the coefficient is positive and statistically significant regardless of the shock direction, whereas the relation with oil price expectations (OPEX) differs across positive and negative shocks, although only the negative shock coefficient is statistically significant. Overall, these results suggest that conventional firm characteristics continue to explain an important part of the heterogeneity in oil shock exposure, while their effects vary depending on the underlying source of the oil market disturbance.

To summarize, these findings imply that firms' risk profile, investment frictions and valuation characteristics are closely related to how sensitive they are to shocks to the oil market. When analyzing firms' exposure to oil-related risks, it is crucial to take the direction of oil market disturbances into consideration. This is further supported by the observed asymmetries between positive and negative oil shocks.

C Bivariate portfolio analysis

While the previous analysis identifies the types of firms that are more exposed to oil market shocks, it remains unclear whether the return differences associated with oil shock exposure simply reflect these underlying firm characteristics. To address this question, we perform bivariate portfolio sorts. Specifically, stocks are first sorted into deciles based on a given firm characteristic and subsequently sorted into deciles according to their estimated oil shock exposure within each characteristic group. We then construct High–Low portfolios based on oil betas within each characteristic decile and average the resulting seven-factor alphas across deciles. This approach examines whether the return differences associated with oil shock exposure persist after controlling for standard firm characteristics and therefore provides a robustness check for the pricing of oil-related risk. The results are presented in Table A2.

Panel A of Table A2 reports results based on unconditional oil betas, which ignore the distinction between positive and negative oil shock realization. These results provide only weak evidence that oil-related risk is priced after controlling for firm characteristics. Most oil shock measures lose statistical significance, in-

Table A1: Average stock characteristics

Variable	OSUP	ODEM	OINV	OP1M	OPEX	OFD-S	ONEW
Panel A. Positive shocks							
Intercept	**-0.25**	**-0.21**	**0.43**	**-12.58**	**-10.34**	**-0.69**	**-0.68**
	(2.78)	(3.78)	(4.34)	(3.09)	(2.13)	(3.75)	(2.90)
β^{MKT}	0.03	**0.03**	-0.03	1.45	-0.05	**0.07**	0.09
	(0.89)	(2.65)	(1.16)	(1.90)	(0.04)	(2.17)	(1.52)
$\beta^{MKT,-}$	0.00	**-0.03**	**0.06**	**-0.61**	-0.18	**-0.07**	-0.06
	(0.13)	(8.66)	(3.99)	(2.67)	(0.37)	(4.50)	(1.87)
SIZE	**0.09**	0.01	**-0.07**	0.80	0.01	**0.11**	-0.01
	(7.22)	(1.10)	(5.09)	(1.74)	(0.02)	(7.12)	(0.32)
BM	**0.07**	0.01	**-0.10**	**1.69**	-1.00	-0.04	-0.02
	(3.27)	(1.06)	(4.31)	(4.29)	(1.52)	(1.65)	(0.54)
OP	0.00	0.00	**0.03**	0.14	0.40	-0.01	-0.04
	(0.07)	(1.08)	(2.16)	(1.01)	(1.33)	(1.18)	(1.71)
REV	0.00	0.00	0.00	0.02	0.03	0.00	0.00
	(0.05)	(0.98)	(0.21)	(0.84)	(0.59)	(0.69)	(0.95)
MOM	0.00	0.00	0.00	0.02	0.03	0.00	0.00
	(1.62)	(1.13)	(0.42)	(1.02)	(0.77)	(1.20)	(0.85)
FMAX	-1.19	0.58	-0.03	54.12	20.76	-1.86	2.62
	(0.76)	(1.01)	(0.02)	(1.61)	(0.35)	(0.91)	(0.79)
IVOL	-0.02	-0.01	0.04	-0.32	-0.52	-0.02	0.05
	(1.28)	(0.76)	(1.95)	(0.77)	(0.69)	(1.07)	(1.19)
LIQ	0.00	**0.00**	0.00	0.00	0.00	0.00	**0.00**
	(1.28)	(2.15)	(0.76)	(0.44)	(0.47)	(1.23)	(2.44)
IRRINV	-0.06	**0.12**	-0.07	**7.37**	**5.79**	-0.05	**0.59**
	(1.63)	(6.60)	(1.94)	(5.73)	(11.04)	(1.11)	(6.43)
MISP	**-0.01**	**0.00**	0.00	**0.08**	**0.14**	0.00	**0.01**
	(5.09)	(5.63)	(0.57)	(2.91)	(2.78)	(0.79)	(3.98)

Note: This table reports the time-series averages of monthly cross-sectional slope coefficients obtained by regressing estimated firm-level oil shock betas on a set of firm characteristics following Bali et al. (2017). Panel A reports results for positive oil shock betas ($\beta^{\mathrm{OIL},+}$), while Panel B reports results for negative oil shock betas ($\beta^{\mathrm{OIL},-}$). The dependent variable is estimated separately for each oil shock measure (OSUP, ODEM, OINV, OP1M, OPEX, OFD-S, and ONEW). Explanatory variables include the market beta (β^{MKT}), downside market beta ($\beta^{\mathrm{MKT},-}$), firm size (SIZE), book-to-market ratio (BM), operating profitability (OP), idiosyncratic volatility (Ivol), investment irreversibility (IRRINV), and the mispricing measure (MISP). Newey–West corrected t-statistics are reported in parentheses. Bold values indicate statistical significance at the 5% level.

Table A1: Average stock characteristics - continued

Variable	**OSUP**	**ODEM**	**OINV**	**OP1M**	**OPEX**	**OFD-S**	**ONEW**
Panel B. Negative shocks							
Intercept	**-0.32**	**-0.09**	**0.21**	**-5.11**	**-4.60**	0.09	0.08
	(6.44)	(4.38)	(4.49)	(4.68)	(2.62)	(1.04)	(0.78)
β^{MKT}	**0.05**	**0.03**	**-0.07**	-0.33	-0.16	**-0.04**	**0.15**
	(6.13)	(9.83)	(5.47)	(1.91)	(0.44)	(2.78)	(8.10)
$\beta^{MKT,-}$	**-0.05**	**-0.03**	**-0.02**	**-0.54**	**-2.27**	**-0.06**	**-0.16**
	(11.04)	(17.42)	(2.44)	(5.74)	(13.74)	(10.99)	(15.64)
SIZE	**0.04**	0.00	0.01	**1.49**	**1.08**	**0.05**	**0.09**
	(6.31)	(0.82)	(1.61)	(9.10)	(5.39)	(6.35)	(6.41)
BM	**0.08**	0.00	**-0.09**	**0.89**	**0.90**	**0.11**	**0.11**
	(10.28)	(0.55)	(8.20)	(5.09)	(3.20)	(5.49)	(5.62)
OP	0.00	0.00	**0.03**	**0.10**	**0.51**	0.00	**-0.04**
	(0.16)	(1.83)	(4.67)	(2.38)	(4.80)	(0.95)	(2.15)
REV	0.00	0.00	0.00	0.02	0.02	0.00	0.00
	(0.14)	(0.09)	(0.73)	(0.66)	(0.35)	(0.88)	(0.63)
MOM	0.00	**0.00**	0.00	0.00	0.00	**0.00**	0.00
	(0.56)	(2.23)	(0.70)	(0.29)	(0.28)	(3.57)	(1.28)
FMAX	0.43	0.15	-0.47	4.49	1.32	4.32	3.72
	(0.36)	(0.35)	(0.32)	(0.21)	(0.03)	(1.86)	(1.45)
IVOL	-0.02	0.00	-0.02	**-0.64**	-0.24	**-0.05**	**-0.10**
	(1.47)	(0.79)	(1.31)	(2.48)	(0.46)	(2.13)	(3.18)
LIQ	0.00	0.00	**0.00**	0.00	0.00	**0.00**	0.00
	(1.30)	(0.71)	(5.88)	(1.01)	(1.26)	(6.06)	(0.35)
IRRINV	**0.12**	**0.02**	**-0.20**	**-2.26**	**-0.89**	**-0.24**	**-0.09**
	(6.64)	(4.03)	(8.08)	(8.15)	(2.73)	(9.09)	(2.83)
MISP	0.00	**0.00**	**0.00**	**-0.04**	**0.05**	**-0.01**	**-0.01**
	(1.50)	(8.12)	(7.67)	(4.29)	(2.84)	(4.26)	(6.72)

dicating that combining positive and negative realizations masks the underlying cross-sectional relation. Only inventory demand shocks (OINV) remain consistently positive and statistically significant across all control variables, while oil forecast disagreement (OFD-S) continues to exhibit significantly negative High–Low alphas for several characteristic sorts.

Once oil shocks are decomposed into positive and negative realizations, a much stronger pattern becomes apparent. Panels B and C of Table A2 show that the High–Low abnormal return disparities linked to directional oil shock exposure are still statistically significant after controlling for a variety of stock characteristics. This indicates that the pricing of directional oil-related risk cannot be explained solely by conventional return predictors. In particular, panel B shows strong evidence for positive global demand shocks (ODEM) and positive one-month oil price changes (OP1M). The corresponding High–Low portfolios remain negative and statistically significant irrespective of the control characteristic, demonstrating that these pricing effects are remarkably robust to differences in market risk, size, value, profitability, momentum, liquidity, investment frictions and mispricing. By contrast, the effects associated with positive oil supply shocks (OSUP), oil price expectations (OPEX) and oil supply news (ONEW) remain significant only for selected characteristic sorts, while the pricing of positive inventory demand shocks (OINV) largely disappears after controlling for firm characteristics. Panel C reveals a different pattern. The strongest and most persistent effects are observed for negative one-month oil price changes (OP1M) and negative oil price expectations (OPEX), both of which remain statistically significant across nearly all characteristic sorts. In contrast, negative global demand shocks (ODEM) lose much of their significance relative to Panel B, while negative inventory demand shocks (OINV) and oil supply news (ONEW) remain significant only after controlling for a limited set of firm characteristics.

Overall, the bivariate portfolio analysis confirms that the cross-sectional pricing of oil-related risk is highly asymmetric. Conditioning on the direction of oil market shocks substantially strengthens the evidence relative to the unconditional specification, and the documented return differences remain robust after controlling for a broad range of firm characteristics. These findings reinforce the conclusion that the sign of an oil shock constitutes an important dimension of systematic risk rather than simply reflecting differences in firms' observable characteristics.

Comment: The bivariate results indicate that inventory-demand shocks are more sensitive to controls for firm characteristics, whereas the pricing of global demand shocks and oil price changes remains robust. This suggests that the latter capture independent sources of systematic risk, while the former may partly reflect differences in firms' underlying characteristics.

Table A2: Bivariate portfolio analysis

Panel A. All shocks							
Variable	OSUP	ODEM	OINV	OP1M	OPEX	OFD-S	ONEW
β^{MKT}	0.00	-0.01	**0.27**	-0.03	0.10	-0.23	0.10
	(-0.02)	(-0.09)	(2.46)	(-0.20)	(0.82)	(-1.53)	(0.90)
$\beta^{MKT,-}$	0.07	-0.04	**0.31**	0.02	0.12	-0.25	0.12
	(0.55)	(-0.40)	(2.77)	(0.14)	(0.86)	(-1.57)	(0.98)
SIZE	0.07	-0.13	**0.22**	-0.16	0.06	-0.18	-0.10
	(0.68)	(-1.19)	(2.11)	(-1.03)	(0.46)	(-1.27)	(-0.81)
BM	0.07	-0.07	**0.45**	0.07	0.14	**-0.30**	0.08
	(0.60)	(-0.68)	(4.33)	(0.48)	(1.13)	(-2.26)	(0.72)
OP	0.01	-0.21	**0.41**	0.06	0.16	**-0.36**	0.08
	(0.13)	(-1.95)	(4.23)	(0.41)	(1.37)	(-2.82)	(0.68)
REV	0.07	-0.11	**0.27**	-0.11	0.06	**-0.44**	0.06
	(0.53)	(-1.01)	(2.40)	(-0.76)	(0.47)	(-2.99)	(0.53)
MOM	0.14	-0.05	**0.27**	0.00	0.01	**-0.38**	0.08
	(0.94)	(-0.49)	(2.17)	(0.01)	(0.09)	(-2.38)	(0.69)
FMAX	0.03	-0.16	**0.23**	0.08	0.11	-0.18	0.08
	(0.24)	(-1.62)	(2.38)	(0.57)	(0.99)	(-1.37)	(0.72)
IVOL	-0.06	-0.05	**0.22**	0.05	0.11	-0.21	0.04
	(-0.65)	(-0.55)	(2.35)	(0.37)	(0.93)	(-1.68)	(0.39)
LIQ	0.11	-0.19	**0.33**	-0.05	-0.06	-0.24	-0.06
	(0.83)	(-1.70)	(2.85)	(-0.30)	(-0.41)	(-1.59)	(-0.46)
IRRINV	0.02	-0.11	**0.51**	0.12	0.16	-0.25	0.06
	(0.15)	(-1.01)	(4.73)	(0.77)	(1.28)	(-1.76)	(0.49)
MISP	0.07	-0.15	**0.55**	0.09	0.17	**-0.29**	0.18
	(0.58)	(-1.47)	(4.98)	(0.67)	(1.44)	(-2.13)	(1.64)

Note: For each oil shock, stocks are first sorted into deciles based on one of the control variables, then within each control deciles, stocks are further sorted into deciles based on their estimated oil beta β^{OIL}. This table reports the risk-adjusted returns (7-factor alpha) difference between the highest and lowest oil beta portfolios (High–Low), averaged over the ten control deciles. The control variables are defined in Section 3.2. In Panel A, the original oil shocks are used to estimate oil beta. In Panel B and C, oil shocks are separated into positive and negative shocks. Newey-West adjusted t-statistics are reported in parentheses. Bold values indicate statistical significance at the 5% level.

Table A2: Bivariate portfolio analysis - continued

Panel B. Positive shocks							
Variable	OSUP	ODEM	OINV	OP1M	OPEX	OFD-S	ONEW
β^{MKT}	-0.16	**-0.42**	0.06	**-0.40**	-0.26	-0.10	**-0.22**
	(-1.45)	(-2.88)	(0.59)	(-2.63)	(-1.80)	(-0.64)	(-1.81)
$\beta^{MKT,-}$	-0.19	**-0.46**	0.14	**-0.58**	-0.27	-0.12	**-0.28**
	(-1.54)	(-2.76)	(1.27)	(-3.43)	(-1.73)	(-0.76)	(-2.00)
SIZE	-0.12	**-0.40**	-0.02	**-0.49**	-0.24	-0.04	-0.20
	(-0.96)	(-3.16)	(-0.21)	(-3.29)	(-1.82)	(-0.26)	(-1.81)
BM	-0.18	**-0.44**	0.18	**-0.51**	-0.16	-0.20	**-0.27**
	(-1.58)	(-3.15)	(1.62)	(-3.40)	(-1.17)	(-1.29)	(-2.31)
OP	**-0.27**	**-0.34**	0.10	**-0.52**	-0.15	-0.20	-0.15
	(-2.41)	(-2.62)	(0.93)	(-3.82)	(-1.14)	(-1.34)	(-1.50)
REV	**-0.30**	**-0.37**	0.12	**-0.49**	**-0.34**	-0.22	**-0.26**
	(-2.51)	(-2.72)	(1.00)	(-3.24)	(-2.30)	(-1.49)	(-2.28)
MOM	-0.13	**-0.33**	0.16	**-0.43**	-0.19	-0.23	-0.14
	(-1.20)	(-2.38)	(1.43)	(-2.84)	(-1.70)	(-1.51)	(-1.33)
FMAX	**-0.25**	**-0.38**	0.08	**-0.42**	**-0.26**	-0.15	-0.14
	(-2.35)	(-2.96)	(0.81)	(-3.30)	(-2.28)	(-1.03)	(-1.17)
IVOL	-0.18	**-0.28**	0.06	**-0.34**	-0.17	-0.21	-0.14
	(-1.84)	(-2.36)	(0.64)	(-2.94)	(-1.46)	(-1.58)	(-1.35)
LIQ	-0.10	**-0.58**	0.15	**-0.58**	**-0.30**	-0.06	**-0.29**
	(-0.78)	(-3.68)	(1.33)	(-3.37)	(-1.99)	(-0.35)	(-2.26)
IRRINV	-0.24	**-0.41**	0.18	**-0.55**	-0.21	-0.14	-0.19
	(-1.91)	(-2.78)	(1.44)	(-3.34)	(-1.22)	(-0.86)	(-1.52)
MISP	**-0.25**	**-0.49**	**0.26**	**-0.58**	-0.16	-0.15	-0.23
	(-2.14)	(-3.18)	(2.19)	(-3.80)	(-1.08)	(-1.07)	(-1.94)

Table A2: Bivariate portfolio analysis - continued

Panel C. Negative shocks							
Variable	OSUP	ODEM	OINV	OP1M	OPEX	OFD-S	ONEW
β^{MKT}	-0.14	**-0.27**	-0.17	**-0.44**	**-0.35**	-0.04	-0.25
	(-1.44)	(-1.99)	(-1.63)	(-2.88)	(-2.35)	(-0.28)	(-1.80)
$\beta^{MKT,-}$	**-0.19**	**-0.30**	-0.21	**-0.57**	**-0.36**	-0.01	-0.30
	(-1.95)	(-2.01)	(-1.82)	(-3.58)	(-2.21)	(-0.06)	(-1.80)
SIZE	-0.08	-0.16	-0.14	**-0.29**	-0.23	-0.03	-0.12
	(-0.95)	(-1.47)	(-1.31)	(-2.09)	(-1.74)	(-0.19)	(-0.82)
BM	-0.16	-0.18	-0.22	**-0.71**	**-0.39**	-0.01	-0.26
	(-1.72)	(-1.36)	(-2.22)	(-4.68)	(-2.68)	(-0.06)	(-1.84)
OP	-0.15	-0.11	-0.18	**-0.63**	**-0.40**	-0.06	-0.20
	(-1.73)	(-0.95)	(-1.88)	(-4.64)	(-3.28)	(-0.48)	(-1.64)
REV	**-0.21**	-0.24	-0.12	**-0.46**	**-0.31**	0.18	**-0.38**
	(-2.17)	(-1.73)	(-0.96)	(-3.27)	(-2.04)	(1.16)	(-2.70)
MOM	-0.22	-0.27	-0.13	**-0.41**	-0.17	0.02	-0.22
	(-1.90)	(-1.94)	(-1.22)	(-2.29)	(-1.49)	(0.15)	(-1.41)
FMAX	**-0.19**	-0.24	-0.15	**-0.41**	**-0.38**	-0.01	**-0.32**
	(-2.24)	(-1.87)	(-1.43)	(-3.01)	(-2.89)	(-0.08)	(-2.17)
IVOL	-0.12	-0.19	-0.11	**-0.33**	**-0.29**	0.01	-0.21
	(-1.54)	(-1.81)	(-1.11)	(-2.73)	(-2.40)	(0.06)	(-1.66)
LIQ	-0.15	**-0.30**	-0.20	**-0.42**	-0.28	-0.01	-0.20
	(-1.52)	(-2.21)	(-1.65)	(-2.51)	(-1.76)	(-0.05)	(-1.32)
IRRINV	-0.12	-0.21	**-0.28**	**-0.73**	**-0.44**	0.01	-0.21
	(-1.23)	(-1.50)	(-2.47)	(-4.27)	(-2.67)	(0.06)	(-1.41)
MISP	-0.16	-0.20	**-0.26**	**-0.65**	**-0.36**	0.03	**-0.29**
	(-1.75)	(-1.60)	(-2.51)	(-4.12)	(-2.37)	(0.19)	(-2.22)