Oil and Equity Return Predictability: The Importance of Dissecting Oil Price Changes*

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Abstract

Based on data until the mid 2000s, oil price changes were shown to predict international equity index returns with a negative predictive slope. Extending the sample to 2015, we document that this relationship has been reversed over the last ten years and therefore has not been stable over time. We then posit that oil price changes are still useful for forecasting equity returns once complemented with relevant information about oil supply and global economic activity. Using a structural VAR approach, we decompose oil price changes into oil supply shocks, global demand shocks, and oil-specific demand shocks. The hypothesis that oil supply shocks and oil-specific demand shocks (global demand shocks) predict equity returns with a negative (positive) slope is supported by the empirical evidence over the 1986–2015 period. The results are statistically and economically significant and do not appear to be consistent with time-varying risk premia.

JEL Classification Codes: C53; G10; G12; G14; E44; Q41
Keywords: Equity return predictability; structural VAR model; oil price change decomposition; oil supply shock; global demand shock; oil-specific demand shock

1 Introduction

As the world's major source of energy, oil plays a crucial role in the modern global economy. Not surprisingly, the impact of oil price fluctuations on equity markets and the real economy has been of great interest to academics, policy makers, and market participants alike. Oil price changes could be interpreted in different ways. On the one hand, an oil price increase could be considered bad news for the economy and equity markets as it increases the cost of production in a significant number of sectors and causes consumers to reduce their consumption. Following the same line of thinking, an oil price drop would have the opposite effect and would be perceived as good news. On the other hand, higher oil prices imply higher profits for the oil sector. This would likely cause oil price shares to gain value and, to some extent, boost the aggregate market. Analogously, lower oil prices is bad news for the oil sector and could negatively affect the broader market. The conventional wisdom in the past was that the former effect dominates, implying that an oil price hike is considered to be bad news for equity markets. Accordingly, a possible hypothesis is that positive (negative) oil price changes should predict lower (higher) subsequent stock returns. In line with this hypothesis, Driesprong, Jacobsen, and Maat (2008) document that, based on data until 2003, oil price changes predict Morgan Stanley Capital International (MSCI) equity index returns with a negative and statistically significant predictive slope for a large number of countries. However, the relationship between oil price movements and subsequent stock returns has not been stable over time. Figure 1, where we present the two scatter plots of the MSCI World index return versus the one-month lagged log growth rate of West Texas Intermediate (WTI) spot price over the 1982–2003 and 2004–2015 periods, clearly illustrates the shift over time. The correlation has shifted from -0.22 in the former period to 0.25 in the latter period. As a result of this shift, the overall predictive ability of oil price change has dramatically decreased over the sample period covering the last thirty years. This structural change is striking and begs for an explanation.

At the most fundamental level, oil prices move when there is a misalignment between supply and demand. Understanding what causes oil price changes, in the first place, can be crucial for determining the potential impact of such a change on equity markets. For instance, lower oil prices due to a slowdown in global economic activity should be viewed as bad news. However, prices could also fall because of excess supply of oil, in which case the message would be different. To provide an explanation for the recent positive correlation between oil price changes and aggregate US market returns, Bernanke (2016) decomposes oil price change into a demand-related component and a residual. He documents that the correlations of the two components with market returns are different and states: "*That's consistent with the idea that when stock traders respond to a change in oil prices, they do so not necessarily because the oil movement is consequential in itself, but because fluctuations in oil prices serve as indicators of underlying global demand and growth.*" Recent academic literature has also discussed the potential differential effects of demand and supply shocks associated with oil price fluctuations. Although oil price shocks were often associated with oil production disruptions in the 1970s and 1980s, it has been argued that the role of global demand for oil, especially from fast-growing emerging economies, should also be emphasized (see Hamilton (2003), Kilian (2009), and Kilian and Park (2009)). Furthermore, the last two papers point out that oil supply shocks, global demand shocks, and other types of shocks, all of which can cause oil prices to fluctuate, should have differential effects on the macroeconomy and the stock market.

In this paper, we investigate whether oil price changes contain useful information for predicting future equity returns. Building on the ideas discussed above, we posit that this is indeed the case, once these changes are suitably decomposed into supply and demand shocks. We motivate the research question by first demonstrating that the negative relationship between oil price changes and future G7 country and World MSCI index excess returns, documented using data until 2003, has dramatically changed over the extended sample period ending in 2015. Faced with this empirical result, one might infer oil price changes are useless for forecasting international equity index returns. However, we contend that information contained in oil price changes becomes useful once it is suitably complemented with relevant information about oil supply and global economic activity. The key observation, as made by Kilian (2009), is that oil price changes are driven by various supply and demand shocks that play fundamentally different roles. Accordingly, we use two distinct structural VAR models that allow us to decompose oil price changes into oil supply, global demand, and oil-specific demand shocks. We, subsequently, illustrate the ability of these three shocks to predict G7 country and World MSCI index excess returns, using metrics of both statistical and economic significance, as well as the structural stability of this predictive relationship over the last thirty years.

Our work relates to a growing literature that examines the impact of oil price shocks on the real economy and equity markets. Chen, Roll, and Ross (1986), Jones and Kaul (1996), and Kilian and Park (2009), among others, examine the contemporaneous relationship between the price of oil and stock prices.[1] Kilian and Park (2009) augment the structural VAR model of Kilian (2009) by incorporating the US real stock return and study the contemporaneous relationships between shocks embedded in oil price changes and stock returns. They examine cumulative impulse responses of real stock returns to one-time shocks to oil supply, global demand, and oil-specific demand in the crude oil market. Their results, using data over the 1975–2006 period, show that an unexpected decrease in oil production has no significant effect on cumulative US real stock returns and a positive surprise to global demand (oil-specific demand) is associated with a subsequent increase (decrease) in US real stock returns. In addition, several recent papers, including Driesprong, Jacobsen, and Maat (2008), Casassus and Higuera (2012), and Narayan and Gupta (2015), investigate the ability of oil price shocks to forecast equity index returns and document a negative predictive slope of oil price changes. Unlike Kilian and Park (2009), and in line with the recent finance literature and Driesprong, Jacobsen, and Maat (2008) in particular, we use a predictive regression framework to examine whether information contained in oil price changes can be used to forecast future stock returns. We approach the question from the perspective of an investor who wishes to use real-time information embedded in oil price changes and captured by the three aforementioned shocks to forecast MSCI equity index excess returns.

This paper is also related to some recent empirical research that focuses on disentangling the intrinsic shocks embedded in oil price changes. Kilian (2009) identifies oil shocks using a structural VAR model and highlights the importance of disentangling oil supply, global demand, and oil-specific demand shocks. However, the short-run price elasticity of oil supply is assumed to be equal to zero in Kilian (2009), implying that oil supply shocks only account for a small fraction

[1] The contemporaneous relationship between the volatility of oil prices and stock returns has been studied by several papers, such as Chiang, Hughen, and Sagi (2015) and Christoffersen and Pan (2017).

of oil price variation. Caldara, Cavallo, and Iacoviello (2017) and Baumeister and Hamilton (2017) propose structural VAR models that facilitate estimation of both oil supply and oil demand elasticities. They further illustrate that the percentage of variation in oil prices attributed to oil supply shocks critically relies on the oil supply and demand elasticity estimates. Rapaport (2014) and Ready (2018) propose to use information from the stock market to identify the underlying types of shocks in oil price changes. Rapaport (2014) identifies shocks specific to the oil market and shocks that affect the overall economy using the sign and magnitude of the correlation between daily oil price changes and aggregate stock market returns, excluding oil companies. Ready (2018) uses crude oil futures returns, returns on a global equity index of oil producing firms, and innovations to the VIX index to identify demand and supply shocks. He documents a strong *contemporaneous* relationship between aggregate market returns and the demand/supply shocks from his decomposition based on data from 1986 to 2011, an empirical result that is readily confirmed to remain valid over the sample period extending to 2015. However, the shocks identified by Ready (2018) cannot forecast future stock market returns. In contrast, the focus of our paper is the *predictive* relationship between the various shocks embedded in oil price changes and equity index returns. Hence, we find that the structural VAR approach along the lines of Kilian (2009), which utilizes more direct proxies for oil supply and global demand and does not require stock market information to obtain the decomposition, is more suitable for our purposes.

In this paper, we make a number of contributions to the literature studying the relationship between oil price fluctuations and subsequent international equity returns. First, we document that the ability of oil price changes to forecast G7 country and World MSCI index returns has dramatically changed over the last decade. In particular, using formal structural break tests, we detect a break in the predictive relationship in the third quarter of 2008 for most of the indexes under examination. Second, using two distinct structural VAR models, we obtain decompositions of oil price changes into oil supply, global demand, and oil-specific demand shocks. The first model is a variant of the Kilian (2009) model, and the second model is a parsimonious version of the model proposed by Caldara, Cavallo, and Iacoviello (2017), which allows for joint estimation of the elasticity of oil supply and demand. The implementation of the structural VAR models is facilitated by the use of suitable proxies for the variables of interest. We use the first principal component of the log growth rates of WTI, Dubai, and Arab Light spot prices as a comprehensive proxy for oil price change. Moreover, we employ two proxies for global real economic activity, namely a shipping cost index and global crude steel production, and use the first principal component of their log growth rates as a comprehensive proxy for global demand growth. Importantly, all the variables that we use in our empirical tests are constructed based on information available in real time. Third, we illustrate the ability of these three shocks to predict G7 country and World MSCI index returns, denominated in both local currency and US dollars. In particular, using the shocks obtained from both structural VAR models, we find empirical evidence supporting the hypothesis that oil supply shocks and oil-specific demand shocks (global demand shocks) predict equity returns with a negative (positive) slope over the 1986–2015 period. We also demonstrate the advantage of using the oil price decomposition instead of just the oil price change, in economic terms, by the economically substantial and statistically significant improvement in the performance of mean-variance optimal trading strategies. Finally, we examine various other aspects of the predictive relationship. To address real-time data availability concerns, we construct returns with a delay of one and two weeks and show that the results are essentially identical. We demonstrate that, as the forecasting horizon increases from one to six months, the predictive ability of the three shocks gradually diminishes. For the case of the US, we document that the forecasting ability is present in the cross section of industries and robust in the presence of standard macroeconomic predictors. The estimated conditional expected returns, based on the three shocks, exhibit high volatility and low persistence in comparison to risk premia estimates available in the literature. Finally, these three shocks do not appear to have an effect on conditional return volatility. Collectively, these results do not appear to be consistent with the notion of time-varying risk premia.

The rest of the paper proceeds as follows. In Section 2, we describe the data that we use in our empirical exercises. In Section 3, we present evidence on the forecasting ability of oil price changes and how it has changed over the last decade. In Section 4, we use structural VAR models to decompose oil price changes into oil supply shocks, global demand shocks, and oil-specific demand shocks. In Section 5, we illustrate the ability of these three types of shocks to forecast MSCI equity index returns and provide additional robustness checks. In Section 6, we offer some concluding remarks.

2 Data

We use five different data sets: returns on international equity indexes, short-term interest rates, oil price proxies, proxies for global economic activity, and global oil production. The full sample period is from January 1982 to December 2015.

We use returns on the G7 country and World MSCI equity indexes, denominated in both local currency and US dollars.[2] We collect monthly short-term interest rates for the G7 countries from the International Monetary Fund (IMF) and the Organisation for Economic Cooperation and Development (OECD). We use IMF Treasury Bill rates whenever available and short-term interest rates obtained from the OECD otherwise.[3]

We further use three proxies for oil price, namely the WTI spot price, the Dubai spot price, and the Arab Light spot price.[4] Note that 75% (83%) of the log growth rates of WTI (Arab Light) prices from October 1973 to September 1981 are zero.[5] Therefore, it is problematic to use WTI and Arab Light prices before September 1981. Therefore, in our empirical analysis, we use oil price data from 1982 onward. Following Driesprong, Jacobsen, and Maat (2008), we use nominal oil prices.

We combine the information contained in the three proxies for crude oil spot price into a single proxy using Principal Component Analysis (PCA). The single proxy, denoted by $g^{\mathtt{P}}$ where $\mathtt{P}$ stands for price, is represented by the first principal component of the log growth rates of WTI, Dubai, and Arab Light spot prices. The details of the construction of the single PCA proxy for oil price change are provided in Appendix A.1. To make the proxy $g^{\mathtt{P}}$ comparable to the three individual proxies, we rescale it so that its standard deviation equals 0.09 over the sample period

[2] Specifically, data on MSCI indexes for the G7 countries, i.e., Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States, as well as the World MSCI index are obtained from Datastream. [3] For Canada, France, Italy, Japan, and the United Kingdom, we use Treasury Bill rates from the IMF. For Germany, we use Treasury Bill rates from the IMF and, from September 2007, short-term interest rates from the OECD. For the United States, we use the 1-month Treasury Bill rate taken from Kenneth French's website. [4] Data on the Dubai and Arab Light spot prices are obtained from Bloomberg. Data on WTI spot oil prices for the period of between January 1982 and August 2013 are obtained from the website of St. Louis Fed. Data for the period between August 2013 and December 2015 are obtained from Bloomberg. [5] Hamilton (2013) documents that the US federal control of crude oil prices started in August 1971 and ended in January 1981.

of January 1983 to December 2015. Table 1 presents summary statistics, including correlations, for g^{P} and the log growth rates of the three oil price proxies. Over the subsample period ending in April 2003, which is the last month in the sample used in Driesprong, Jacobsen, and Maat (2008), as well as the full sample period, g^{P} is highly correlated with the log growth rates of the three individual proxies. The top panel in Figure 2 also shows that the four series track each other quite closely.

We use two proxies for global economic activity to capture changes in global demand. The first proxy is a shipping cost index constructed from data on dry cargo single voyage rates and the Baltic Dry Index (BDI). Since the supply of bulk carriers is largely inelastic, fluctuations in dry bulk cargo shipping cost are thought to reflect changes in global demand for transporting raw materials such as metals, grain, and coal by sea. Therefore, shipping cost is considered to be a useful leading indicator of global economic activity. Data on dry cargo single voyage rates are hand collected from Drewry Shipping Statistics and Economics for the period between January 1982 and January 1985. Rates for seven representative routes are reported each month. We compute the monthly log growth rates of the shipping cost for each route, and then, following Kilian (2009), obtain the cross-sectional equally-weighted average.[6] Data on the BDI from January 1985 to December 2015 are obtained from Bloomberg.

The second proxy for global economic activity is global crude steel production. Ravazzolo and Vespignani (2015) argue that world steel production is a good indicator of global real economic activity. Steel is widely used in a number of important industries, such as energy, construction, automotive and transportation, infrastructure, packaging, and machinery. Therefore, fluctuations in world crude steel production reflect changes in global real economic activity. We obtain monthly crude steel production data for the period January 1990 to December 2015 from the World Steel Association's website. The reported monthly figure represents crude steel production in 66 countries and accounts for about 99% of total world crude steel production. In addition, monthly data for the period January 1968 to October 1991 are hand collected from the Steel Statistical Yearbook published by the International Iron and Steel Institute. Crude steel pro-

[6] It is, however, worth noting that there is an important difference between our proxy for global economic activity and the one constructed in Kilian (2009). Specifically, in Kilian (2009), the average growth rate is cumulated, then deflated, using the US CPI, and finally detrended. In that sense, the proxy in Kilian (2009) is a level variable. In contrast, our proxy is a growth rate.

duction exhibits strong seasonality and, therefore, we seasonally adjust the data, as we explain in Appendix A.1.

As in the case of oil price proxies, we use PCA to construct a single proxy for global demand growth. The single proxy, denoted by $g^{\mathtt{GD}}$ where GD stands for global demand, is represented by the first principal component of the log growth rates of the shipping cost index and global crude steel production. The details of the construction of the single PCA proxy for global demand growth are provided in Appendix A.1. The correlations between $g^{\mathtt{GD}}$ and the log growth rates of the shipping cost index and global crude steel production are 0.82 and 0.74, respectively. The bottom panel in Figure 2 shows that $g^{\mathtt{GD}}$ closely tracks the two individual proxies most of time, except for a few instances in which one of the two proxies takes extreme values.

Finally, we obtain oil production data, covering the period between January 1982 and December 1991, from the website of the US Energy Information Agency.[7] In addition, we hand-collect data on the total supply of crude oil, natural gas liquids, processing gains, and global biofuels, for the period between December 1991 and December 2015, from the monthly Oil Market Report obtained from the website of the International Energy Agency. Combining data from the two sources, we construct a time series of monthly log growth rates of world crude oil production.

3 Oil price change as a predictor of MSCI index excess returns

To examine whether oil price changes can predict equity returns, we start by revisiting the evidence documented in Driesprong, Jacobsen, and Maat (2008) who consider a sample period ending in April 2003. In particular, we estimate the following standard predictive regression model:

$$r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{P}} + \delta^{\mathtt{P}} g^{\mathtt{P}}_t + u^{\mathtt{P}}_{t+1}, \tag{1}$$

where $r^{\mathtt{e}}_{t+1}$ is the excess return on an MSCI index and the oil price change proxy $g^{\mathtt{P}}_t$ is the first principal component obtained from three oil spot price log growth rates: WTI, Dubai, and Arab Light. We construct excess returns by subtracting the particular country's short-term rate from

[7] Specifically, we use Table 11.1b (World Crude Oil Production: Persian Gulf Nations, Non-OPEC, and World).

each MSCI index return in the case of local currency-denominated indexes and by subtracting the US Treasury Bill rate from each MSCI index return in the case of US dollar-denominated indexes.[8]

We consider the MSCI indexes for the G7 countries as well as the World MSCI index, denominated both in local currencies and US dollars. The oil price change proxy we use is the first principal component obtained from the WTI, Dubai, and Arab Light spot prices, as explained in Section 2. Driesprong, Jacobsen, and Maat (2008) document negative and statistically significant estimates of the predictive slope coefficient δ^{P} for a large number of countries based on a sample that ends in April 2003. We first run the predictive regression for the sample starting in January 1983 and ending in April 2003 and then consider the extended sample period starting in January 1983 and ending in December 2015. We examine the statistical significance of predictability in terms of p-values and adjusted R-squares. Furthermore, we examine the economic significance of predictability by evaluating the performance of the resulting optimal trading strategies in terms of certainty equivalent returns and Sharpe ratios. Appendix A.2 explains in detail the methods used to evaluate predictive ability.

3.1 Evidence from the 1983–2003 sample period

In the left panel of Table 2, we present statistical significance results for the predictive regression model (1) based on MSCI index excess returns, denominated in both local currencies and US dollars over the sample period starting in January 1983 and ending in April 2003. We first focus our analysis on this sample period to facilitate comparison of our results with the evidence presented in Driesprong, Jacobsen, and Maat (2008) who also use a sample ending in April 2003.

For local currency-denominated returns, the point estimate of the predictive slope δ^{P} in regression (1) is negative for all six cases. The null hypothesis $H_0 : \delta^{\mathsf{P}} = 0$ is rejected in six (four) out of six cases at the 10% (5%) level of significance according to Newey and West (1987) standard errors. When Hodrick (1992) standard errors are used, $H_0 : \delta^{\mathsf{P}} = 0$ is rejected in five (four) out of six cases at the 10% (5%) level of significance; Japan yields the highest p-value equal to 0.12. The

[8] While Driesprong, Jacobsen, and Maat (2008) use log returns in their empirical analysis, it is more convenient for us to use excess returns for the purpose of assessing the economic significance of the predictive ability of oil price changes. The results for log returns, available upon request, are very similar.

adjusted R-square is greater than 2% in five out of six cases; Canada yields the lowest adjusted R-square equal to 1%. The results for US dollar-denominated returns are qualitatively similar.[9] Note that our empirical exercise differs from the analysis in Driesprong, Jacobsen, and Maat (2008) in that we use our own oil price change proxy, our sample starts at a different point in time, and we use excess returns as opposed to log returns. Despite these differences, our results confirm their evidence on the relationship between oil price changes and subsequent global equity returns for the sample period ending in April 2003.

In the left panel of Table A1 in the Online Appendix, we present evidence on the ability of oil price changes to predict MSCI index excess returns in terms of economic significance, over the 1983.01–2003.04 period. Specifically, we report results on the certainty equivalent return (CER) and the Sharpe ratio (SR) of the associated optimal trading strategies for a mean-variance investor with a risk aversion coefficient $\gamma = 3$ (see Appendix A.2). These results reinforce the statistical significance results reported in the left panel of Table 2. Let $\mathtt{CER}_{\mathtt{IID}}$ and $\mathtt{SR}_{\mathtt{IID}}$ denote the CER and SR achieved by the optimal trading strategy assuming that the MSCI index excess returns are i.i.d., and $\mathtt{CER}_{\mathtt{P}}$ and $\mathtt{SR}_{\mathtt{P}}$ denote the CER and SR achieved by the optimal trading strategy using the predictive regression model (1). For local currency-denominated returns, the alternative model using the oil price change proxy g^{P} as predictor generates significantly higher (point estimates of) CERs and SRs compared to the baseline model that assumes that MSCI index excess returns are i.i.d. across all six countries. More importantly, the null hypothesis $H_0^{\mathsf{CER}} : \mathtt{CER}_{\mathtt{IID}} = \mathtt{CER}_{\mathtt{P}}$ is rejected in six (five) out of six cases at the 10% (5%) level of significance, respectively, against the one-sided alternative $H_A^{\mathsf{CER}} : \mathtt{CER}_{\mathtt{IID}} < \mathtt{CER}_{\mathtt{P}}$. The null hypothesis $H_0^{\mathsf{SR}} : \mathtt{SR}_{\mathtt{IID}} = \mathtt{SR}_{\mathtt{P}}$ is rejected against the one-sided alternative $H_A^{\mathsf{SR}} : \mathtt{SR}_{\mathtt{IID}} < \mathtt{SR}_{\mathtt{P}}$ in all six cases at the 5% level of significance.[10]

[9] Specifically, the point estimate of the predictive slope δ^{P} in regression (1) is negative for all eight cases. The null hypothesis $H_0 : \delta^{\mathsf{P}} = 0$ is rejected in seven (six) out of eight cases at the 10% (5%) level of significance according to Newey and West (1987) standard errors. When Hodrick (1992) standard errors are used, $H_0 : \delta^{\mathsf{P}} = 0$ is rejected in six (six) out of eight cases at the 10% (5%) level of significance; Japan again yields the highest p-value equal to 0.27. The adjusted R-square is greater than 2% in six out of eight cases; Canada yields the lowest adjusted R-square equal to 0.7%. Importantly, for the case of the World MSCI index, $H_0 : \delta^{\mathsf{P}} = 0$ is strongly rejected by both methods and the adjusted R-square is equal to 5.6%, which is rather high for monthly returns.

[10] The results for US dollar-denominated returns are qualitatively similar. The alternative model based on the predictive regression model (1) still generates significantly higher (point estimates of) CERs and SRs compared to the baseline i.i.d. model for MSCI index excess returns across all eight cases. The null hypothesis $H_0^{\mathsf{CER}} : \mathtt{CER}_{\mathtt{IID}} = \mathtt{CER}_{\mathtt{P}}$ is rejected in five (three) out of eight cases at the 10% (5%) level of significance, respectively, against the one-sided alternative $H_A^{\mathsf{CER}} : \mathtt{CER}_{\mathtt{IID}} < \mathtt{CER}_{\mathtt{P}}$, with Canada yielding the highest p-value equal to 0.15. The null hypothesis $H_0^{\mathsf{SR}} : \mathtt{SR}_{\mathtt{IID}} = \mathtt{SR}_{\mathtt{P}}$ is rejected against the one-sided alternative $H_A^{\mathsf{SR}} : \mathtt{SR}_{\mathtt{IID}} < \mathtt{SR}_{\mathtt{P}}$ in six (three) out of eight cases at the 10% (5%) level of significance, respectively, with Japan yielding the highest p-value equal to 0.14.

Overall, the economic significance results confirm the evidence reported in Driesprong, Jacobsen, and Maat (2008) on the ability of oil price changes to forecast international equity index returns.

3.2 Evidence from the 1983–2015 sample period

In this subsection, we extend the sample period to December 2015 and run the same predictive regressions again. As in the previous subsection, we examine both the statistical and economic significance of the predictive ability of oil price changes.

In the right panel of Table 2, we present statistical significance results over the 1983.01–2015.12 period. The evidence obtained from the extended sample is quite different: the predictive ability of oil price changes has mostly disappeared.

For local currency-denominated returns, the point estimates of the predictive slope δ^{P} in regression (1) are still negative for all six countries. However, they are much smaller in absolute value. For instance, for Japan and the UK, the δ^{P} point estimates obtained over the 1983.01–2003.04 period are -0.11 and -0.11, while they fall to -0.05 and -0.06 over the 1983.01–2015.12 period, respectively. The null hypothesis $H_0 : \delta^{\mathsf{P}} = 0$ is now rejected in only three (two) out of six cases at the 10% (5%) level of significance according to Newey and West (1987) standard errors. Moreover, we observe a substantial reduction in adjusted R-squares. For instance, for Japan and the UK, the adjusted R-squares obtained over the 1983.01–2003.04 period are 2.9% and 4.1%, while they fall to 0.3% and 1.4% over the 1983.01–2015.12 period, respectively. In the case of Canada, the adjusted R-square even becomes negative.

The results for US dollar-denominated returns are even weaker. While the δ^{P} point estimates are still negative in seven out of eight cases, they are even smaller in absolute value than their counterparts obtained for local currency-denominated returns and, in the case of Canada, the predictive slope estimate becomes positive. The null hypothesis $H_0 : \delta^{\mathsf{P}} = 0$ is rejected only in the case of Italy at the 10% level of significance, regardless of whether we use Newey and West (1987) or Hodrick (1992) standard errors. Importantly, the corresponding p-values for the US and the World MSCI indexes are 0.22 and 0.22, respectively, according to Newey and West (1987) standard errors. In addition, the adjusted R-squares are rather low: they are less than 1% in seven out of eight cases, and even negative in the case of Canada. Hence, our results show substantially weaker statistical evidence on the relationship between oil price changes and subsequent global equity excess returns over the 1983.01–2015.12 period compared to the 1983.01–2003.04 period.

The right panel of Table A1 in the Online Appendix reports results on the economic significance of the predictive ability of oil price changes, over the 1983.01–2015.12 sample period, in terms of the CER and the SR of the associated optimal trading strategies for a mean-variance investor with a risk aversion coefficient $\gamma = 3$ (see Appendix A.2). These results reinforce the message, conveyed by the right panel of Table 2, that the forecasting ability of oil price changes has all but disappeared over the extended sample ending in December 2015. For local currency-denominated returns, the null hypothesis $H_0^{\mathsf{CER}} : \mathtt{CER}_{\mathtt{IID}} = \mathtt{CER}_{\mathtt{P}}$ is *not* rejected against the one-sided alternative $H_A^{\mathsf{CER}} : \mathtt{CER}_{\mathtt{IID}} < \mathtt{CER}_{\mathtt{P}}$ in four out of six cases at the 10% level of significance, with the exceptions of Italy and the UK. We obtain the same results when we test $H_0^{\mathsf{SR}} : \mathtt{SR}_{\mathtt{IID}} = \mathtt{SR}_{\mathtt{P}}$ against $H_A^{\mathsf{SR}} : \mathtt{SR}_{\mathtt{IID}} < \mathtt{SR}_{\mathtt{P}}$. The results for US dollar-denominated returns are even weaker. The null hypothesis $H_0^{\mathsf{CER}} : \mathtt{CER}_{\mathtt{IID}} = \mathtt{CER}_{\mathtt{P}}$ is *not* rejected against the one-sided alternative $H_A^{\mathsf{CER}} : \mathtt{CER}_{\mathtt{IID}} < \mathtt{CER}_{\mathtt{P}}$ in any case, out of eight, at the 10% level of significance. Importantly, the corresponding p-values for the US and the World MSCI indexes are 0.37 and 0.30, respectively.

Collectively, the statistical as well as economic significance results presented in this subsection illustrate that the forecasting ability of oil price changes has been diminished over the extended sample ending in December 2015. In the next subsection, we provide further corroborating evidence by examining the stability, or lack thereof, of the predictive relationship between MSCI index excess returns and past oil price changes.

3.3 Instability of the predictive slope coefficients

The empirical evidence gathered in the previous two subsections suggests that the ability of oil price changes to predict MSCI index excess returns is not stable over time. We confirm previous results on the oil price change predictive ability using data until April 2003, consistent with the evidence in Driesprong, Jacobsen, and Maat (2008), but also show that these results do not hold in the extended sample ending in December 2015. While we obtain negative and statistically significant predictive slope estimates in the early sample, these estimates become much closer to zero and lose their statistical significance in the extended sample.

As a first attempt to shed some light on these striking findings, we estimate the predictive regression model (1) over different samples using an expanding window. The first sample covers the 1983.01–1993.01 period and the last sample covers the 1983.01–2015.12 full period. Figures A1 and A2, both in the Online Appendix, present the predictive slope estimates along with 95% confidence intervals, based on Newey and West (1987) standard errors, over the period 1993.01–2015.12 for local currency- and US dollar-denominated MSCI index returns, respectively. The pattern evident in these graphs is rather revealing. For the majority of the cases, the predictive slope estimates are negative and frequently statistically significant until the third quarter of 2008. For most cases after that point in time, however, the estimates start increasing to zero and quickly lose their statistical significance. This effect is more prominent for US dollar-denominated returns.

In addition to the informal analysis based on the predictive slope estimates presented in the aforementioned graphs, we also perform formal structural break tests. Specifically, we employ the methodology developed by Bai and Perron (2003) to test for multiple structural breaks in the predictive slope coefficients. The Bayesian Information Criterion (BIC) is used to select the number of breaks.

Table 3 presents Bai and Perron (2003) structural break tests in the slope coefficient for the predictive regression (1). The second column presents the BIC values assuming no break. The third and fourth columns provide the BIC values and the corresponding break dates for the case of the one-break model. The last column shows the number of breaks selected by the BIC. For local currency-denominated index returns, the test identifies the presence of one structural break in five out of six cases, with the only exception of the UK. For US dollar-denominated index returns, the test identifies the presence of one structural break in seven out of eight cases, with the only exception of France. The break dates identified in most cases fall in the third quarter of 2008. However, the break dates for Italy and Japan are October 2003 and September 1990, respectively. Overall, the structural break tests provide additional evidence against the stability of the slope coefficient in the predictive relationship between MSCI index excess returns and past oil price changes.

4 Identifying oil price shocks using structural VAR models

In the previous section, we confirm the finding of Driesprong, Jacobsen, and Maat (2008) that oil price changes predict international equity index returns at the monthly frequency with a negative predictive slope based on data up to April 2003. However, we also provide compelling evidence that the predictive power of oil price changes has practically disappeared over the extended sample ending in December 2015. For most of the MSCI indexes, the predictive slope estimates based on expanding windows become closer to zero and turn statistically insignificant after the third quarter of 2008. Moreover, the formal econometric tests of Bai and Perron (2003) indicate the existence of a structural break in the third quarter of 2008 for the majority of the cases, especially when US dollar-denominated returns are used. The dramatic reduction in the predictive ability of oil price changes, therefore, begs for an explanation.

In this paper, we offer an explanation that emphasizes the differential roles of the various shocks embedded in oil price changes. Specifically, we use a structural Vector Autoregression (VAR) framework that provides a decomposition of oil price changes into oil supply shocks, global demand shocks, and oil-specific demand shocks. As Kilian (2009) and Kilian and Park (2009) point out, oil price shocks cannot be treated as strictly exogenous with respect to the global economy. In particular, they argue that oil supply shocks, global demand shocks, and oil-specific demand shocks, the combination of which leads to the observed aggregate oil price changes, should have different effects on the macroeconomy and the stock market.

Kilian and Park (2009) augment the structural VAR model of Kilian (2009) by adding the US real stock return in the vector of variables and study the contemporaneous relationships between shocks embedded in oil price changes and stock returns. They further examine cumulative impulse responses of real stock returns to one-time shocks to oil supply, global demand, and oil-specific demand in the crude oil market. Their results, using data over the 1975–2006 period, show that an unexpected decrease in oil production has no significant effect on cumulative US real stock returns and a positive surprise to global demand (oil-specific demand) leads to a continuous increase (decrease) in US real stock returns. In this paper, following the recent finance literature, Driesprong, Jacobsen, and Maat (2008) in particular, we cast the question in a predictive regression framework using short-horizon, i.e., one-month-ahead, forecasts. Although we utilize the structural VAR framework along the lines of Kilian (2009), we approach the question from the perspective of an investor who wishes to use the real-time information embedded in oil price changes and captured by the three aforementioned shocks to predict subsequent equity index returns.

To disentangle the supply shocks, demand shocks, and oil-specific demand shocks embedded in the observed oil price changes, we employ two distinct structural VAR models. The first model is a variant of the Kilian (2009) model which assumes that the short-run elasticity of oil supply is zero. The second model is a parsimonious version of the model proposed by Caldara, Cavallo, and Iacoviello (2017) that allows for joint estimation of the elasticities of oil supply and oil demand. Both of the structural VAR models describe the joint evolution of three variables capturing changes in the (i) supply of oil; (ii) global economic activity; and (iii) price of oil. The first variable, denoted by $g_t^{\mathtt{S}}$, where S stands for supply, is the log growth rate of world crude oil production. The second variable, denoted by $g_t^{\mathtt{GD}}$, where GD stands for global demand, is the first principal component of the log growth rates of the dry bulk cargo shipping cost index and global crude steel production. It has been argued in the literature, e.g., Kilian (2009) and Ravazzolo and Vespignani (2015), among others, that fluctuations in shipping cost and global crude steel production capture changes in global economic activity growth and demand for oil. The third variable, denoted by $g_t^{\mathtt{P}}$ where P stands for price, is the first principal component of the log growth rates of West Texas Intermediate, Dubai, and Arab Light spot prices. We provide a detailed explanation of the data sources and construction in Section 2.

Our purpose is to employ the two structural VAR models to obtain a decomposition of oil price changes into three types of shocks and use them as predictors of MSCI index returns. We do so by, first, using information available in real time and, second, constructing three variables that are stationary in a consistent way as explained above. As a result, our approach differs from Kilian (2009) and Caldara, Cavallo, and Iacoviello (2017) who use detrended level variables. Importantly, as Apergis and Miller (2009) point out, the variables of global real economic activity and log real oil price used in the structural VAR model in Kilian (2009) appear to be non-stationary. On the contrary, our variables are, by construction, stationary.

4.1 Structural VAR framework

Let $\mathbf{g}_t = [g_t^{\mathtt{S}} \quad g_t^{\mathtt{GD}} \quad g_t^{\mathtt{P}}]'$ denote the vector of the three variables described above. The structural VAR model is then stated as:

$$\mathbf{A}_0 \mathbf{g}_t = \mathbf{a} + \sum_{i=1}^{p} \mathbf{A}_i \mathbf{g}_{t-i} + \boldsymbol{\varepsilon}_t, \tag{2}$$

where $\mathbf{A}_0$ is the 3×3 matrix specifying the contemporaneous structural relations between the three variables, $\mathbf{a} = [a_{\mathtt{S}} \quad a_{\mathtt{GD}} \quad a_{\mathtt{P}}]'$ is a 3×1 vector, $\mathbf{A}_i = [\mathbf{a}_{i,\mathtt{S}} \quad \mathbf{a}_{i,\mathtt{GD}} \quad \mathbf{a}_{i,\mathtt{P}}]'$ is a 3×3 matrix, for $i = 1, \ldots, p$, and $\boldsymbol{\varepsilon}_t = [\varepsilon_t^{\mathtt{S}} \quad \varepsilon_t^{\mathtt{GD}} \quad \varepsilon_t^{\mathtt{OSD}}]'$ is the vector of orthogonal structural shocks. The interpretation of the fundamental shocks is as follows: $\varepsilon_t^{\mathtt{S}}$ is the oil supply shock, $\varepsilon_t^{\mathtt{GD}}$ is the global demand shock, and $\varepsilon_t^{\mathtt{OSD}}$ is the oil-specific demand shock. The structural innovation vectors $\boldsymbol{\varepsilon}_t$ are, by assumption, serially and cross-sectionally uncorrelated with covariance matrix given by

$$\boldsymbol{\Sigma}_\varepsilon = \mathrm{Var}[\boldsymbol{\varepsilon}_t] = \begin{bmatrix} \sigma_{\mathtt{S}}^2 & 0 & 0 \\ 0 & \sigma_{\mathtt{GD}}^2 & 0 \\ 0 & 0 & \sigma_{\mathtt{OSD}}^2 \end{bmatrix}. \tag{3}$$

The reduced-form VAR innovation obtained from the structural VAR model (2) is $\mathbf{e}_t = \mathbf{A}_0^{-1} \boldsymbol{\varepsilon}_t$. Letting $\boldsymbol{\Sigma}_e$ denote the covariance matrix of $\mathbf{e}_t$, we obtain $\boldsymbol{\Sigma}_e = \mathbf{A}_0^{-1} \boldsymbol{\Sigma}_\varepsilon (\mathbf{A}_0^{-1})'$ which is the equation that provides identification of the matrices of interest $\mathbf{A}_0$ and $\boldsymbol{\Sigma}_\varepsilon$. Note that the covariance matrix $\boldsymbol{\Sigma}_e$ contains six distinct parameters. Due to the orthogonality of the structural shocks, $\boldsymbol{\Sigma}_\varepsilon$ contains three distinct parameters. Hence, only three distinct parameters in the matrix $\mathbf{A}_0$ can be identified. We consider two different structural VAR models reflected in the form of the matrix $\mathbf{A}_0$. The first model is a variant of the model advanced by Kilian (2009) and assumes zero short-term oil supply elasticity; it is referred to as the IS model, where IS stands for inelastic supply of oil. The second model is a parsimonious version of the recent model proposed by Caldara, Cavallo, and Iacoviello (2017) that facilitates joint identification of oil supply and demand elasticities; it is referred to as the ES model, where ES stands for elastic supply of oil. For now, we assume that the matrix $\mathbf{A}_0$ is fully identified, given knowledge of the covariance matrix $\mathbf{\Sigma}_e$. We elaborate more on how $\mathbf{A}_0$ is determined in the context of both models below.

The estimation of the VAR model and the decomposition of oil price changes proceed as follows. Multiplying both sides of the structural VAR model (2) by $\mathbf{A}_0^{-1}$ yields the reduced-form VAR model

$$\mathbf{g}_t = \mathbf{b} + \sum_{i=1}^{p} \mathbf{B}_i \mathbf{g}_{t-i} + \mathbf{e}_t, \tag{4}$$

where $\mathbf{b} = \mathbf{A}_0^{-1}\mathbf{a}$ and $\mathbf{B}_i = \mathbf{A}_0^{-1}\mathbf{A}_i$, $i = 1, \ldots, p$. The parameters $\mathbf{b}$ and $\mathbf{B}_i$ are estimated by standard OLS and the VAR order p is selected using the BIC criterion. The matrix $\mathbf{\Sigma}_e$ is estimated by the covariance matrix of the residuals from (4). Writing the VAR(p) system in VAR(1) form, we obtain

$$\mathbf{y}_t = \mathbf{C}\mathbf{y}_{t-1} + \mathbf{u}_t, \tag{5}$$

where $\mathbf{y}_t$ and $\mathbf{u}_t$ are $3p \times 1$ vectors defined by

$$\mathbf{y}_t = [\ \mathbf{g}_t' - \boldsymbol{\mu}_g' \quad \mathbf{g}_{t-1}' - \boldsymbol{\mu}_g' \quad \cdots \quad \mathbf{g}_{t-p+1}' - \boldsymbol{\mu}_g'\ ]', \tag{6}$$

$$\mathbf{u}_t = [\ \mathbf{e}_t' \quad \mathbf{0}_3' \quad \cdots \quad \mathbf{0}_3'\ ]', \tag{7}$$

$\boldsymbol{\mu}_g$ is the mean of $\mathbf{g}_t$ and $\mathbf{C}$ is a suitable $3p \times 3p$ matrix (involving the matrices $\mathbf{B}_i$, $i = 1, \ldots, p$). The Wold representation of $\mathbf{y}_t$ reads $\mathbf{y}_t = \sum_{i=0}^{\infty} \mathbf{C}^i \mathbf{u}_{t-i}$. Denoting by $\mathbf{D}_i$ the 3×3 upper-left block of the matrix $\mathbf{C}^i$ and defining the matrix $\mathbf{F}_i = \mathbf{D}_i \mathbf{A}_0^{-1}$, we can express $\mathbf{g}_t$ as $\mathbf{g}_t = \boldsymbol{\mu}_g + \sum_{i=0}^{\infty} \mathbf{F}_i \boldsymbol{\varepsilon}_{t-i}$. The third element of the vector $\mathbf{g}_t$ is the oil price change proxy denoted by $g^{\mathtt{P}}$. Hence, we obtain the following decomposition of $g^{\mathtt{P}}$ into three components

$$g_t^{\mathtt{P}} = \mu_g^{\mathtt{P}} + x_t^{\mathtt{S}} + x_t^{\mathtt{GD}} + x_t^{\mathtt{OSD}}, \tag{8}$$

where $\mu_g^{\mathtt{P}}$ is the mean of the oil price change $g_t^{\mathtt{P}}$, $x_t^{\mathtt{S}} = \sum_{i=0}^{\infty} (\mathbf{F}_i)_{31} \varepsilon_{t-i}^{\mathtt{S}}$ is the oil supply shock, $x_t^{\mathtt{GD}} = \sum_{i=0}^{\infty} (\mathbf{F}_i)_{32} \varepsilon_{t-i}^{\mathtt{GD}}$ is the global demand shock, and $x_t^{\mathtt{OSD}} = \sum_{i=0}^{\infty} (\mathbf{F}_i)_{33} \varepsilon_{t-i}^{\mathtt{OSD}}$ is the oil-specific demand shock.

As mentioned above, the reduced-form VAR model (4) is estimated using standard OLS. In our implementation, the order p is selected equal to 2 according to BIC.

4.2 Inelastic supply (IS) structural VAR model

The identification strategy in Kilian (2009) rests on the following assumptions: (i) oil production does not respond contemporaneously to either global demand or oil price changes; (ii) global demand responds contemporaneously to oil production but not to oil price changes; and (iii) oil price responds contemporaneously to both oil production and global demand changes. Importantly, according to Kilian (2009)'s setting, the short-run elasticity of oil supply is assumed to be zero. Note that the above restrictions imply that the matrix $\mathbf{A}_0$ in the IS model is lower triangular:

$$\mathbf{A}_0^{\mathtt{IS}} = \begin{bmatrix} 1 & 0 & 0 \\ \vartheta & 1 & 0 \\ \varrho & \varphi & 1 \end{bmatrix}. \tag{9}$$

Recall that the matrices $\mathbf{A}_0$ and $\mathbf{\Sigma}_\varepsilon$ are identified through the equation $\mathbf{\Sigma}_e = \mathbf{A}_0^{-1}\mathbf{\Sigma}_\varepsilon(\mathbf{A}_0^{-1})'$. Hence, given the form of $\mathbf{A}_0^{\mathtt{IS}}$, one can use the Cholesky factor of the covariance matrix $\mathbf{\Sigma}_e$ to recover both $\mathbf{A}_0^{\mathtt{IS}}$ and $\mathbf{\Sigma}_\varepsilon$.

4.3 Elastic supply (ES) structural VAR model

While Kilian (2009) has successfully emphasized the importance of disentangling oil demand and supply shocks, it has also received criticism in the literature regarding the assumption of inelastic supply of oil. One of the implications of the model is that oil supply shocks account for a rather small percentage of variation in oil prices (see Ready (2018), Caldara, Cavallo, and Iacoviello (2017), and Baumeister and Hamilton (2017), among others). To address these concerns, we also consider a structural VAR model that facilitates estimation of both oil supply and demand elasticities. The model is a parsimonious version of the model proposed by Caldara, Cavallo, and

Iacoviello (2017). The three equations describing the joint evolution of $\mathbf{g}_t$ are:

$$g_t^{\mathtt{S}} = \eta_{\mathtt{S}} g_t^{\mathtt{P}} + a_{\mathtt{S}} + \sum_{i=1}^{p} \mathbf{a}'_{i,\mathtt{S}} \mathbf{g}_{t-i} + \varepsilon_t^{\mathtt{S}}, \tag{10}$$

$$g_t^{\mathtt{S}} = \eta_{\mathtt{D}} g_t^{\mathtt{P}} + \theta g_t^{\mathtt{GD}} + a_{\mathtt{P}} + \sum_{i=1}^{p} \mathbf{a}'_{i,\mathtt{P}} \mathbf{g}_{t-i} + \varepsilon_t^{\mathtt{OSD}}, \tag{11}$$

$$g_t^{\mathtt{GD}} = \lambda g_t^{\mathtt{S}} + a_{\mathtt{GD}} + \sum_{i=1}^{p} \mathbf{a}'_{i,\mathtt{GD}} \mathbf{g}_{t-i} + \varepsilon_t^{\mathtt{GD}}. \tag{12}$$

Equations (10) and (11) characterize the oil market. Equation (10) describes the oil supply schedule. We assume that oil production reacts contemporaneously only to oil price changes. The short-run price elasticity of oil supply is captured by the parameter $\eta_{\mathtt{S}}$. Equation (11) describes the oil demand schedule. We assume that oil demand responds contemporaneously to both oil price changes and changes in global economic activity. The short-run price elasticity of oil demand is captured by the parameter $\eta_{\mathtt{D}}$. Equation (12) describes the evolution of global economic activity. We assume that global economic activity is affected contemporaneously only by changes in oil production. The corresponding $\mathbf{A}_0$ matrix is given by

$$\mathbf{A}_0^{\mathtt{ES}} = \begin{bmatrix} 1 & 0 & -\eta_{\mathtt{S}} \\ -\lambda & 1 & 0 \\ 1 & -\theta & -\eta_{\mathtt{D}} \end{bmatrix}. \tag{13}$$

As emphasized by Caldara, Cavallo, and Iacoviello (2017), the parameters in $\mathbf{A}_0^{\mathtt{ES}}$ cannot be jointly identified without additional information. However, the ES model is very informative in the sense that it imposes restrictions on the feasible pairs of elasticities $(\eta_{\mathtt{S}}, \eta_{\mathtt{D}})$. Indeed, assuming a value for $\eta_{\mathtt{S}}$ and knowledge of the covariance matrix $\mathbf{\Sigma}_e$, one can recover the rest of the parameters in $\mathbf{A}_0^{\mathtt{ES}}$ according to the equation $\mathbf{A}_0 \mathbf{\Sigma}_e \mathbf{A}_0' = \mathbf{\Sigma}_\varepsilon$. This procedure results in an admissible set of pairs $(\eta_{\mathtt{S}}, \eta_{\mathtt{D}})$ that are consistent with the ES structural VAR model. To determine estimates of supply and demand elasticities consistent with their structural VAR model, Caldara, Cavallo, and Iacoviello (2017) propose a two-stage identification strategy. First, they obtain independent estimates $(\eta^*_{\mathtt{S}}, \eta^*_{\mathtt{D}})$ using an instrumental variable (IV) estimation approach.[11] Then, they select the optimal admissible pair of elasticities $(\widehat{\eta}_{\mathtt{S}}, \widehat{\eta}_{\mathtt{D}})$ by minimizing a suitable distance between the admissible pairs and $(\eta^*_{\mathtt{S}}, \eta^*_{\mathtt{D}})$, i.e., solving the following problem:

$$\min_{\eta_{\mathtt{S}}} \begin{bmatrix} \eta_{\mathtt{S}} - \eta^*_{\mathtt{S}} \\ \eta_{\mathtt{D}}(\eta_{\mathtt{S}}; \mathbf{\Sigma}_e) - \eta^*_{\mathtt{D}} \end{bmatrix}' \mathbf{V}^{-1} \begin{bmatrix} \eta_{\mathtt{S}} - \eta^*_{\mathtt{S}} \\ \eta_{\mathtt{D}}(\eta_{\mathtt{S}}; \mathbf{\Sigma}_e) - \eta^*_{\mathtt{D}} \end{bmatrix}, \tag{14}$$

where $\eta_{\mathtt{D}}(\eta_{\mathtt{S}}; \mathbf{\Sigma}_e)$ is the elasticity of demand consistent with $\eta_{\mathtt{S}}$ and $\mathbf{\Sigma}_e$, and $\mathbf{V}$ is a diagonal matrix of weights that reflect the sampling error in the $(\eta^*_{\mathtt{S}}, \eta^*_{\mathtt{D}})$ estimates. Adopting the identification procedure advanced by Caldara, Cavallo, and Iacoviello (2017) to our setting and using their IV point estimates $(\eta^*_{\mathtt{S}}, \eta^*_{\mathtt{D}}) = (0.077, -0.074)$, we obtain the set of admissible pairs as well as the optimal admissible pair of elasticities $(\widehat{\eta}_{\mathtt{S}}, \widehat{\eta}_{\mathtt{D}}) = (0.157, -0.136)$. The results are presented in Figure 3 that closely resembles Figure 2 in Caldara, Cavallo, and Iacoviello (2017). Even though we use a more parsimonious model, with three instead of five variables, different proxies and cast our VAR model in terms of growth rates as opposed to levels, our estimates of supply and demand elasticities are quite close to the estimates obtained by Caldara, Cavallo, and Iacoviello (2017), i.e., $(\widehat{\eta}_{\mathtt{S}}, \widehat{\eta}_{\mathtt{D}}) = (0.11, -0.13)$. Moreover, our results are comparable to the results in Baumeister and Hamilton (2017) who obtain $(\widehat{\eta}_{\mathtt{S}}, \widehat{\eta}_{\mathtt{D}}) = (0.15, -0.35)$. The rest of the parameters in $\mathbf{A}_0^{\mathtt{ES}}$ and $\mathbf{\Sigma}_e$, namely λ, θ, $\sigma^2_{\mathtt{S}}$, $\sigma^2_{\mathtt{GD}}$, and $\sigma^2_{\mathtt{OSD}}$ are readily recovered from the equation $\mathbf{A}_0 \mathbf{\Sigma}_e \mathbf{A}_0' = \mathbf{\Sigma}_\varepsilon$.

4.4 Oil price decomposition according to the IS and ES models

We obtain estimates of the matrix $\mathbf{A}_0$, in the context of the IS and ES models, as we explain above. Using these estimates and employing equation (8), we decompose oil price changes into oil supply, global demand, and oil-specific demand shocks. The two structural models presented above, IS and ES, have quite different implications in terms of the role of supply shocks in explaining the variation in oil prices. Specifically, our IS model estimates, based on the full sample, imply

[11] Caldara, Cavallo, and Iacoviello (2017) estimate the price elasticity of oil supply and demand by using IV panel regressions. They use a narrative analysis to identify 14 exogenous episodes of large country-specific declines in oil production for 21 countries over the period 1985–2015. In the supply and demand regression equations, for a particular country, the instrumental variables for the price of oil are large exogenous declines in oil production in other countries. In the second stage, country-level IV regressions for supply and demand use changes in crude oil production and petroleum consumption in the particular country, by excluding exogenous episodes involving that country. They obtain point estimates of supply and demand elasticity equal to 0.077 and -0.074, respectively.

that 1%, 5%, and 94% of oil price change variation is attributed to oil supply, global demand, and oil-specific demand shocks, respectively. In contrast, our ES model estimates, based on the full sample, imply that 58%, 5%, and 37% of oil price change variation is explained by oil supply, global demand, and oil-specific demand shocks, respectively. In Figure 4, we present the percentages of the variance of oil price changes attributed to oil supply and oil-specific demand shocks as a function of the elasticity of supply η_S in the context of the ES model. The pattern in Figure 4 illustrates that the percentage of oil price variation explained by oil supply shocks is a monotonically increasing function of the elasticity of supply η_S. The pattern is consistent with the fact that the IS model can be seen a limiting case of the ES model as the elasticity of supply, η_S, approaches zero.

For the purposes of predicting future equity returns, we need estimates of the oil supply, global demand, and oil-specific demand shocks based on available data at each point in time. To obtain such estimates, we estimate the reduced-form VAR model (4) and obtain the decomposition in equation (8) in a real-time fashion for both the IS and ES models. Specifically, for each month in the period between January 1986 and December 2015, we estimate the VAR model using all available data starting in February 1982 and ending in that month. Then, we obtain the time series of three shocks in the decomposition (8), but keep the vector of the oil supply, global demand, and oil-specific demand shocks only for the last month. Our real-time decomposition is obtained in a fashion that reflects all revisions to past data of crude oil and crude steel production. We plot the real-time estimates of the oil supply, global demand, and oil-specific demand shocks from January 1986 to December 2015 in Figure 5. As expected, oil-specific demands shocks are more volatile under the IS model, while oil supply shocks are more volatile under the ES model. The global demand shocks are very similar across the two structural VAR models.

5 The predictive power of oil supply, global demand, and oil-specific demand shocks

In this section, we examine the ability of the three shocks obtained by the oil price change decomposition (8) to forecast next-month MSCI index excess returns over the sample period from January 1986 to December 2015. Specifically, we run the following predictive regression:

$$r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{DEC}} + \beta^{\mathtt{S}} x^{\mathtt{S}}_t + \beta^{\mathtt{GD}} x^{\mathtt{GD}}_t + \beta^{\mathtt{OSD}} x^{\mathtt{OSD}}_t + u^{\mathtt{DEC}}_{t+1}, \tag{15}$$

where $r^{\mathtt{e}}_{t+1}$ denotes excess return on an MSCI index and $x^{\mathtt{S}}_t$, $x^{\mathtt{GD}}_t$, $x^{\mathtt{OSD}}_t$ denote the oil supply, global demand, oil-specific demand shocks obtained from the decomposition (8), respectively. We consider the shocks obtained from both the IS and ES structural VAR models. As in the previous section, we gauge the forecasting ability of the three shocks using measures of both statistical and economic significance. Furthermore, we offer comparisons between model (1), which uses oil price change as the sole predictor, and the decomposition-based model (15).

The three shocks identified by the decomposition (8) are anticipated to have different impacts on future equity returns. Given that demand for oil is less than perfectly elastic, a disruption in oil production would result in an oil price increase. Such a disruption would be potentially bad news for the real economy and the stock market while the corresponding shock $x^{\mathtt{S}}$ would be positive. Hence, one expects $\beta^{\mathtt{S}}$ to have a negative value in the predictive regression (15). Second, positive global demand shocks stimulate the global economy as a whole, although the impact might differ across countries. One, therefore, expects that a positive global demand shock would be good news for equity markets. At the same time, a positive global demand shock could drive up the price of oil, which, in turn, could have a slowing-down effect on certain economies. However, the overall effect should be dominated by the first direct impact and, hence, one expects a positive slope $\beta^{\mathtt{GD}}$ in the predictive regression (15). Third, following the interpretation in Kilian (2009), an oil-specific demand shock is thought to capture changes in the demand for oil driven by precautionary motives. Accordingly, a positive oil-specific demand shock is thought to originate from the increased demand for oil due to uncertainty regarding future availability of oil and is, therefore, perceived as bad news for the global economy and the stock market. Hence, one expects $\beta^{\mathtt{OSD}}$ to have a negative value in the predictive regression (15).

Summarizing the above discussion, we view an oil price increase due to an oil supply or an oil-specific demand shock as bad news. Recall, however, that the two structural VAR models that we use have different implications regarding the magnitude of these shocks. According to the

IS model, the percentages of oil price variation explained by oil supply and oil-specific demand shocks are 1% and 94%, respectively, while, according to the ES model, these percentages are 58% and 37%, respectively. Hence, we anticipate that, when we use the shocks obtained from the IS (ES) model, the oil-specific demand (oil supply) shocks will play a more important role in predicting future equity returns. Indeed, this is confirmed by the evidence presented in the following subsection.

5.1 Evidence on the predictive ability of the shocks obtained from the structural VAR models

In Tables 4 and 5, we present statistical significance results for the predictive regression (15) over the 1986.01–2015.12 sample period using the shocks obtained from the IS and ES models, respectively. To provide a direct comparison between the predictive regression model (1), which uses oil price change as the sole predictor, and the predictive regression model (15), we also estimate model (1) over the same sample period. We report results for MSCI index excess returns denominated in both local currencies and US dollars and compute standard errors using the Newey and West (1987) method with optimal bandwidth selected as in Newey and West (1994).

As expected, given the evidence presented in Section 3, the forecasting power of oil price changes diminishes over the 1986.01–2015.12 sample period. The results are very similar to those presented in Table 2 corresponding to the 1983.01–2015.12 sample period. In particular, the adjusted R-square for both the World and the US MSCI index is 0.5%. In stark contrast, we find strong evidence of predictability using the decomposition-based model (15) with the shocks obtained from either the IS or the ES model.

The results based on the IS model shocks are reported in Table 4 and summarized as follows. We focus on US dollar-denominated returns, as the results for local currency-denominated returns are very similar. The adjusted R-squares for the Canada, France, Germany, Italy, Japan, and UK MSCI indexes are 1.5%, 1.5%, 1.9%, 6.6%, 0.7%, and 2.1%, respectively. The $\beta^{\mathtt{GD}}$ estimates are positive in all eight cases and statistically significant in four (six) cases at the 5% (10%) level of significance. The $\beta^{\mathtt{OSD}}$ estimates are negative in all eight cases and statistically significant in five (six) cases at the 5% (10%) level of significance. The $\beta^{\mathtt{S}}$ estimates are negative in six out of eight cases, although statistically significant only in one case. Importantly, for the US and the World MSCI indexes, the $\beta^{\mathtt{GD}}$ estimate is positive, the $\beta^{\mathtt{OSD}}$ estimate is negative, and both are statistically significant at the 5% level of significance, while the corresponding R-squares are 4.3% and 3.6%, respectively.

The results based on the ES model shocks, reported in Table 5, also show strong predictive ability of the shocks, except that in this case it is the oil supply shock, as opposed to the oil-specific demand shock, that negatively and significantly predicts future equity returns. Next, we briefly summarize the results for US dollar-denominated returns; the results for local currency-denominated returns are very similar. The adjusted R-squares for the Canada, France, Germany, Italy, Japan, and UK MSCI indexes are 1.5%, 1.1%, 1.5%, 6.0%, 0.7%, and 2.3%, respectively. The $\beta^{\mathtt{GD}}$ estimates are positive in all eight cases and statistically significant in four (six) cases at the 5% (10%) level of significance. The $\beta^{\mathtt{S}}$ estimates are negative in all eight cases and statistically significant in four (four) cases at the 5% (10%) level of significance. The $\beta^{\mathtt{OSD}}$ estimates are negative in five out of eight cases, although none of them are statistically significant. Importantly, for the US and the World MSCI indexes, the $\beta^{\mathtt{S}}$ estimate is negative, the $\beta^{\mathtt{GD}}$ estimate is positive, and both are statistically significant at the 5% level of significance, while the corresponding R-squares are 4.2% and 4.1%, respectively.[12]

In addition to the evidence on statistical significance, we also provide evidence on the economic significance of the ability of the oil supply, global demand, and oil-specific demand shocks to predict the G7 country and World MSCI index returns. We refer to the model described by the decomposition-based predictive regression (15) as the alternative model and compare it to three baseline models. The first baseline model assumes that the MSCI index excess return $r^{\mathtt{e}}_{t+1}$ is i.i.d. The second baseline model is described by the predictive regression (1) that uses the oil

[12] We repeat the above analysis, for both the IS and ES models, computing standard errors according to the Hodrick (1992) method. The results, reported in Tables A2 and A3 in the Online Appendix, are similar and convey the same message. Collectively, there is strong statistical evidence supporting the usefulness of the decomposition (8) and the ability of the three associated shocks to forecast the World and G7 country MSCI index excess returns.

price change $g^{\mathtt{P}}$ as predictor. The third baseline model is described by the predictive regression

$$r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{GD}} + \delta^{\mathtt{GD}} g^{\mathtt{GD}}_t + u^{\mathtt{GD}}_{t+1}, \tag{16}$$

which uses the global demand growth proxy $g^{\mathtt{GD}}$ as predictor.

Let $\mathtt{CER}_{\mathtt{DEC}}$ and $\mathtt{SR}_{\mathtt{DEC}}$ denote the CER and SR achieved by the optimal trading strategy for a mean-variance investor with a risk aversion coefficient $\gamma = 3$ using the decomposition-based predictive regression model (15). Analogously, we denote by $\mathtt{CER}_{\mathtt{IID}}$, $\mathtt{CER}_{\mathtt{P}}$, and $\mathtt{CER}_{\mathtt{GD}}$ ($\mathtt{SR}_{\mathtt{IID}}$, $\mathtt{SR}_{\mathtt{P}}$, and $\mathtt{SR}_{\mathtt{GD}}$) the CERs (SRs) achieved by the optimal trading strategies using the i.i.d. model, the predictive regression (1) based on oil price change, and the predictive regression (16) based on global demand growth, respectively. To gauge the predictive ability of the shocks $x^{\mathtt{S}}_t$, $x^{\mathtt{GD}}_t$, and $x^{\mathtt{OSD}}_t$, we test the null hypotheses $H^{\mathtt{CER}}_0 : \mathtt{CER}_{\mathtt{IID}} = \mathtt{CER}_{\mathtt{DEC}}$, $H^{\mathtt{CER}}_0 : \mathtt{CER}_{\mathtt{P}} = \mathtt{CER}_{\mathtt{DEC}}$, and $H^{\mathtt{CER}}_0 : \mathtt{CER}_{\mathtt{GD}} = \mathtt{CER}_{\mathtt{DEC}}$ against their one-sided alternatives. Furthermore, in a similar fashion, we test the null hypotheses $H^{\mathtt{SR}}_0 : \mathtt{SR}_{\mathtt{IID}} = \mathtt{SR}_{\mathtt{DEC}}$, $H^{\mathtt{SR}}_0 : \mathtt{SR}_{\mathtt{P}} = \mathtt{SR}_{\mathtt{DEC}}$, and $H^{\mathtt{SR}}_0 : \mathtt{SR}_{\mathtt{GD}} = \mathtt{SR}_{\mathtt{DEC}}$ against their one-sided alternatives. The economic significance test results, based on the shocks obtained from the IS and ES models, are reported in Tables 6 and 7, respectively. Next, we discuss the results based on the shocks obtained from the IS model. The results based on the shocks obtained from the ES model are similar.

For local currency-denominated index returns, the decomposition-based model (15) generates CERs that are higher than their counterparts generated by the i.i.d. model in all six cases. The difference is sizable, e.g., more than 3.76%, in annualized terms, for Japan and the UK, and statistically significant in five out of six cases at the 10% level of significance. Moreover, the decomposition-based model (15) generates CERs that are higher than their counterparts generated by model (1) based on oil price change in five out of six cases, with the exception of France. In the remaining cases, the difference is greater than 1.2%, in annualized terms, and statistically significant in the case of Japan at the 10% level of significance. The decomposition-based model (15) also performs substantially better than the model (16) based on global demand growth in terms of CER. It produces CERs that are higher in all six cases and statistically significant in four out of six cases at the 10% level of significance. The SR results are in line with the CER results. The decomposition-based model (15) generates SRs that are higher than their counterparts generated by the i.i.d. model in all six cases. The increase in SR is sizable, e.g., from 0.19 to 0.53 for the UK, and the difference is statistically significant in four out of six cases at the 5% level of significance. Moreover, the decomposition-based model (15) generates SRs that are at least as high as their counterparts generated by the model (1) based on oil price change in all six cases. The differences again are sizable and statistically significant in the case of Japan at the 5% level of significance. The decomposition-based model (15) also performs substantially better than the model (16) based on global demand growth in terms of SR. It produces SRs that are higher in all six cases and statistically significant in five out of six cases at the 10% level of significance.

The results for US dollar-denominated index returns convey the same message. Importantly, in the case of the US MSCI index, the decomposition-based model (15) generates an annualized CER equal to 9.28% compared to 6.52%, 6.08%, and 6.20% generated by the i.i.d. model, the predictive regression model (1), and the predictive regression model (16), respectively. The corresponding p-values are 0.11, 0.08, and 0.05, respectively. Even stronger results are obtained for the World MSCI index. The decomposition-based model (15) generates an annualized CER equal to 7.90% compared to 4.03%, 3.88%, and 3.30% generated by the i.i.d. model, model (1), and model (16), respectively. The difference is statistically significant in all three comparisons with p-values equal to 0.04, 0.07, and 0.03, respectively. Strong results are obtained in terms of SR as well. In the case of the US MSCI index, the decomposition-based model (15) generates an annualized SR equal to 0.65 compared to 0.48, 0.45, and 0.46 generated by the i.i.d. model, model (1), and model (16), respectively. The corresponding p-values are 0.12, 0.09, and 0.05, respectively. For the World MSCI index, the decomposition-based model (15) generates an annualized SR equal to 0.56 compared to 0.31, 0.30, and 0.27 generated by the i.i.d. model, model (1), and model (16), respectively. The difference is statistically significant in all three comparisons with p-values equal to 0.04, 0.06, and 0.03, respectively.

Thus far, in this subsection, we have provided strong evidence, in terms of statistical as well as economic significance, in support of the ability of the oil supply, global demand, and oil-specific demand shocks to predict the World and G7 country MSCI index excess returns, based on both IS and ES models. Next, we provide further corroborating evidence on the stability of this predictive relation between MSCI index excess returns and these three shocks. As in the case on the predictive regression model (1), we use the Bai and Perron (2003) methodology to test for structural breaks in the decomposition-based model (15). The results are presented in Table 8. The test identifies breaks in zero (two) out of the 14 cases considered, covering six local currency- and eight US dollar- denominated MSCI indexes, when we use shocks from the IS (ES) model. Collectively, the results illustrate the importance of disentangling oil price changes into oil supply, global demand, and oil-specific demand shocks for the purpose of forecasting international equity returns.

In the next subsection, we examine various aspects of the relationship between the three shocks embedded in oil price changes and future stock returns. In particular, we provide evidence suggesting that the documented predictability does not appear to be consistent with time-varying risk premia.

5.2 Additional evidence and robustness checks

First, to alleviate any concerns regarding the real-time availability of the data required to obtain the oil price change decomposition (8), we estimate the predictive regression $r^{\mathtt{d}}_{t+1} = \alpha^{\mathtt{DEC}} + \beta^{\mathtt{S}} x^{\mathtt{S}}_t + \beta^{\mathtt{GD}} x^{\mathtt{GD}}_t + \beta^{\mathtt{OSD}} x^{\mathtt{OSD}}_t + u^{\mathtt{DEC}}_{t+1}$, where $r^{\mathtt{d}}_{t+1}$ is the monthly net return on the World or a G7 country MSCI index constructed with a delay of one or two weeks.[13] The results for the shocks obtained from the IS and ES models, reported in Tables 9 and 10, respectively, are in line with the baseline evidence reported in Tables 4 and 5. Overall, the results illustrate the robustness of the forecasting ability of oil supply, global demand, and oil-specific demand shocks with respect to one- or two-week delays.

When studying return predictability, one natural question that emerges is whether the predictors under examination can forecast asset returns over horizons longer than one month. We present statistical evidence on the predictive ability, at the three-month and six-month horizons, of the shocks obtained using the IS and ES models in Tables 11 and 12, respectively. The results

[13] We do not use excess returns for this exercise due to lack of availability of interest rate data for the relevant time periods.

show that the predictive ability of the three shocks gradually diminishes as the horizon gets longer. Moreover, the statistical significance of the slope corresponding to the global demand shock decreases as we move from the three-month to the six-month horizon. This evidence is reinforced by the adjusted R-squares over horizons up to six months that we report in Table 13. The adjusted R-squares at the six-month horizon are typically much lower than their three-month counterparts. As argued by Fama and French (1989) and Driesprong, Jacobsen, and Maat (2008), among others, predictability typically associated with time-varying risk premia is long-lived and persists over long horizons. We document that this is not the case for the oil supply, global demand, and oil-specific demand shocks and, hence, we conclude that the documented predictability is not consistent with time-varying risk premia.

We also examine whether the results on the predictability of aggregate equity index returns are robust in the cross section of US industries. Specifically, we use the 17 Fama-French value-weighted industry portfolios.[14]

First, we conduct Bai and Perron (2003) structural break tests for (i) the predictive regression using oil price change as the predictor, for the 1983.01–2015.12 sample period, and (ii) the predictive regression using the oil supply, global demand, and oil-specific demand shocks, obtained from both the IS and ES models, as predictors, for the 1986.01–2015.12 sample period. Table A4 in the Online Appendix shows that the tests identify the presence of one structural break in 14 of 17 industry portfolios when oil price change is used as the sole predictor, with the exception of Mining and Minerals, Oil and Petroleum Products, and Utilities. In contrast, the tests do not identify a break for any industry when the three shocks embedded in oil price changes are used as predictors. Collectively, these results are consistent with the evidence from the G7 country and World MSCI indexes reported in subsection 5.1.

Second, we examine the ability of the three shocks, obtained from the IS and ES models, to forecast industry portfolio excess returns. The results are presented in Tables A5 and A6 in the

[14] We use monthly returns on the 17 Fama-French value-weighted industry portfolios from Kenneth French's website. The abbreviations (descriptions) of the 17 industries are Food (Food), Mines (Mining and Minerals), Oil (Oil and Petroleum Products), Clths (Texiles, Apparel and Footware), Durbl (Consumer Durables), Chems (Chemicals), Cnsum (Drugs, Soap, Perfumes, Tobacco), Cnstr (Construction and Construction Materials), Steel (Steel Works Etc), FabPr (Fabricated Products), Machn (Machinery and Business Equipment), Cars (Automobiles), Trans (Transportation), Utils (Utilities), Rtail (Retail Stores), Finan (Banks, Insurance Companies, and Other Financials), and Other (Other).

Online Appendix, where we also provide the results of the predictive regression using oil price change as the sole predictor, for the purposes of comparison. Given the results of the structural break tests discussed above, the results of the oil price change regression are meaningful only for the three industries that do not exhibit a break. As expected, the estimated predictive slope on oil price change is positive for the Oil and Petroleum Products industry, although not statistically significant. Overall, there is no evidence of predictability based on oil price change alone, with 15 out of 17 adjusted R-squares being less than 1%. In contrast, there exists strong evidence of predictability across the various industries based on the three shocks embedded in oil price changes, according to Newey and West (1987) standard errors. The results for the IS model shocks (Table A5) are summarized as follows. The $\beta^{\texttt{GD}}$ estimates are positive for all 17 industries and statistically significant for 12 (13) industries at the 5% (10%) level. The $\beta^{\texttt{OSD}}$ estimates are negative for 15 industries and statistically significant for seven (eight) industries at the 5% (10%) level. The $\beta^{\texttt{S}}$ estimates are negative for all 17 industries, although statistically significant only for four industries at the 10% level. Moreover, the adjusted R-square is greater than 1.5% for 12 out of 17 industries. The results based on the ES model shocks (Table A6) convey the same message, except that, as in the case of MSCI index returns, it is the oil supply shock, and not the oil-specific demand shock, that negatively predicts industry returns. The $\beta^{\texttt{GD}}$ estimates are positive for all 17 industries and statistically significant for 12 (14) industries at the 5% (10%) level. The $\beta^{\texttt{S}}$ estimates are negative for all 17 industries and statistically significant for seven (eight) industries at the 5% (10%) level. The $\beta^{\texttt{OSD}}$ estimates are negative for 10 industries but not statistically significant for any of them. Finally, the adjusted R-square is greater than 1.5% for 14 out of 17 industries. Overall, these results demonstrate that the predictive ability of the oil supply, global demand, and oil-specific demand shocks is strong not only for the aggregate equity index, but also across different US industry portfolios.

Another natural question in the context of equity return predictability is: how do the proposed predictors relate to macroeconomic variables that have been extensively used in the extant literature to model time-varying expected equity returns? Due to data limitations, we examine this issue only for the case of the US. Table 14 presents the contemporaneous correlations between the oil supply, global demand, and oil-specific demand shocks, obtained from the IS and

ES models in a real-time fashion, and four macroeconomic variables: the log dividend yield, the term spread, the default yield spread, and the one-month Treasury Bill rate. The correlations are rather low in magnitude with the largest (in absolute value) being the correlation between the global demand shock and the default yield equal to -0.17.

In addition, we examine whether the forecasting ability of the oil supply, global demand, and oil-specific demand shocks is robust to the presence of the macroeconomic predictors in the case of the US. We examine the following linear predictive regressions $r^{\mathtt{e}}_{t+1} = \gamma^{\mathtt{P}} + \delta^{\mathtt{P}} g^{\mathtt{P}}_{t} + \boldsymbol{\theta}'\mathbf{z}_t + v^{\mathtt{P}}_{t+1}$ and $r^{\mathtt{e}}_{t+1} = \gamma^{\mathtt{DEC}} + \beta^{\mathtt{S}} x^{\mathtt{S}}_{t} + \beta^{\mathtt{GD}} x^{\mathtt{GD}}_{t} + \beta^{\mathtt{OSD}} x^{\mathtt{OSD}}_{t} + \boldsymbol{\lambda}'\mathbf{z}_t + v^{\mathtt{DEC}}_{t+1}$ over various sample periods, where $r^{\mathtt{e}}_{t+1}$ is the US MSCI index excess return and $\mathbf{z}_t$ is the vector of the four macroeconomic variables mentioned above. The results, based on shocks from both the IS and ES models, are reported in Table 15. According to the evidence, the inference results we have reported thus far in the paper are robust to the presence of the macroeconomic variables. In particular, the forecasting ability of oil price change over the early 1982.01–2003.04 sample period is unaffected. Moreover, over the 1986–2015 sample period, the slopes of the global demand shock and the oil supply (oil-specific demand) shock are positive and negative, respectively, and significant at the 5% level of significance for the ES (IS) model, consistent with our baseline results.

In our next empirical exercise, we examine the descriptive statistics of the conditional expected excess returns based on the oil supply, global demand, and oil-specific demand shocks obtained from the IS and ES models. In particular, we focus on the mean, the standard deviation, and the first three autocorrelations. This evidence can shed light on the issue of whether the documented predictive ability of the three shocks is consistent with time-varying risk premia. For the purposes of comparison, we use two benchmarks. The first benchmark is the predicted MSCI US index excess return based on the aforementioned macroeconomic variables in terms of descriptive statistics. We report the results for the time period 1986.01–2015.12 in Table 16. Overall, the conditional expected excess returns predicted by the three shocks are more volatile and much less persistent compared to their analogues obtained from the macroeconomic variables. One might argue that the predicted excess returns based on the macroeconomic variables are just too persistent, given the nature of these macroeconomic predictors. To address this concern, in our second comparison, we use as a benchmark the equity risk premium estimates obtained by Martin (2017) based on option prices over different maturities, ranging from one month to one year.[15] Table 17 reports the results for the time period 1996.01–2012.01, which is the sample period used by Martin (2017). The main message from the second comparison remains the same. In particular, the second and third order autocorrelations of the conditional expected excess returns predicted by the three shocks are much lower than their counterparts obtained from either the predicted excess returns based on the macroeconomic predictors or the risk premium estimates of Martin (2017). Collectively, this evidence suggests that the forecasting ability of the three shocks is not consistent with time-varying risk premia, in line with the evidence of predictability diminishing over longer horizons as reported above.

We conclude this section by investigating whether there is a more direct link between time variation in expected returns and changes in risk, as captured by return volatility. Such an exercise can shed more light on the question of whether the predictive ability of the oil supply, global demand, and oil-specific demand shocks is associated with changes in risk premia. To this end, we employ an augmented EGARCH(1,1) model that includes these three shocks in the volatility equation as exogenous regressors. If the variation of expected returns is to be attributed to time-varying risk premia, we expect that any of these three shocks would have the same effect on both the drift and the volatility. In the context of the EGARCH model, we expect the coefficient on any of these shocks to have the same sign as in the drift equation and be statistically significant. The econometric specification is:

$$r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{DEC}} + \beta^{\mathtt{S}} x^{\mathtt{S}}_t + \beta^{\mathtt{GD}} x^{\mathtt{GD}}_t + \beta^{\mathtt{OSD}} x^{\mathtt{OSD}}_t + u^{\mathtt{DEC}}_{t+1}, \tag{17}$$

$$u^{\mathtt{DEC}}_{t+1} = \sigma_t z_{t+1}, \quad z_{t+1} \sim \text{i.i.d.}(0,1), \tag{18}$$

$$\log(\sigma^2_t) = \tau_0 + \tau_1 |z_t| + \tau_2 z_t + \tau_3 \log(\sigma^2_{t-1}) + \zeta^{\mathtt{S}} x^{\mathtt{S}}_t + \zeta^{\mathtt{GD}} x^{\mathtt{GD}}_t + \zeta^{\mathtt{OSD}} x^{\mathtt{OSD}}_t. \tag{19}$$

As argued above, time-varying risk premia would be consistent with $\zeta^{\mathtt{S}} < 0$, $\zeta^{\mathtt{GD}} > 0$, and $\zeta^{\mathtt{OSD}} < 0$. We estimate the model using monthly excess returns on the MSCI indexes for the G7 countries as well as the World MSCI index, denominated both in local currencies and US dollars, over the 1986.01–2015.12 sample period. We consider three distributions for the disturbances z_{t+1}: Normal, Student-t, and GED. The Student-t distribution was selected according to the Bayesian

[15] We thank Ian Martin for making the data available on his website.

Information Criterion.[16] The results for the IS and the ES models are presented in Tables A7 and A8 in the Online Appendix, respectively. In the majority of the cases, the estimates $\zeta^{\texttt{S}} < 0$, $\zeta^{\texttt{GD}} > 0$, and $\zeta^{\texttt{OSD}} < 0$ are statistically insignificant at conventional levels. Moreover, for the IS model, whenever there is significance, the sign is the opposite of what would be consistent with time-variation of risk premia; e.g., in five out of 14 instances, the estimates of $\zeta^{\texttt{GD}}$ are statistically significant but negative. This evidence is inconsistent with the notion of time-varying risk premia, reinforcing the message conveyed by the evidence documented earlier.

6 Conclusion

As the modern global economy heavily depends on oil, the price of oil is widely thought to affect global real economic activity and, consequently, the global equity market. An oil price drop, in the past, has been considered as good news, as it lowers the cost of production in a significant number of sectors and allows consumers to boost their consumption. Accordingly, one could hypothesize that negative (positive) oil price changes should predict higher (lower) subsequent equity returns. Driesprong, Jacobsen, and Maat (2008) document that this is indeed the case for a large number of MSCI equity indexes based on data until 2003. However, this predictive relationship has dramatically changed over the last ten years. Specifically, the correlation between the World MSCI index return and the lagged one-month log growth rate of West Texas Intermediate spot price has increased from -0.22 over the 1982–2003 period to 0.25 over the 2004–2015 period. As a result, the ability of oil price change to forecast future equity returns has diminished over the sample period that extends to 2015. Furthermore, using the formal econometric test of Bai and Perron (2003), we detect a structural break in the predictive relationship in the third quarter of 2008 for most of the G7 country MSCI index returns.

In this paper, we suggest that oil price changes do, in fact, contain useful information for forecasting subsequent equity indexes, provided that these changes are suitably disentangled into supply and demand shocks. Using two distinct structural VAR models, we obtain an oil price change decomposition into an oil supply shock, a global demand shock, and an oil-specific de-

[16] The results are very similar across all three distributional assumptions.

mand shock and argue that these three different types of shocks should have different effects on equity markets. The first model is a variant of the model proposed by Kilian (2009), and assumes zero elasticity of oil supply. The second model is a parsimonious version of the model advanced by Caldara, Cavallo, and Iacoviello (2017) that facilitates joint estimation of oil supply and demand elasticities. The hypothesis that oil supply shocks and oil-specific demand shocks (global demand shocks) predict equity returns with a negative (positive) slope is supported by the empirical evidence over the 1986-2015 sample period, using shocks obtained from both structural VAR models. Using the oil price decomposition obtained from the first structural VAR model, instead of just oil price change, leads to an increase of the annualized certainty equivalent return and Sharpe ratio of a mean-variance optimal trading strategy for the World MSCI index from 3.88% to 7.90% and from 0.30 to 0.56, respectively, with the differences being statistically significant. When we use the shocks obtained from the second structural VAR model, the corresponding increases are from 3.88% to 7.67% for the annualized certainty equivalent return and from 0.30 to 0.55 for the Sharpe ratio. These results survive in the presence of traditional macroeconomic predictors for the case of the US MSCI index and, in general, do not appear to be consistent with time-varying risk premia.

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A Appendices

A.1 Data construction

The single oil price change proxy $g^{\mathtt{P}}$ is constructed in a real-time fashion using PCA. Specifically, for each month t between January 1983 and December 2015, we use data on three proxies for oil price change starting in February 1982 and ending in month t. We first rescale the three log growth rates, obtained from the West Texas Intermediate, the Dubai, and the Arab Light spot prices, so they all have variances equal to one over the given sample period and then perform PCA. The first PCA corresponding to month t is kept each time and the process is repeated using expanding windows until December 2015 is reached.

To address the strong seasonality of the global crude steel production data, we use X-13ARIMA-SEATS to compute seasonally-adjusted level data from which we compute log growth rates in a real-time fashion.[17] Specifically, for each month in the period between February 1982 and December 2015, we perform seasonal adjustment on the level data starting in January 1968 and ending in that month, compute the log growth rates of the seasonally adjusted level data, and, finally, keep the log growth rate over the last month.

The single global demand growth proxy $g^{\mathtt{GD}}$ is also constructed in a real-time fashion using PCA. Specifically, for each month t between January 1983 and December 2015, we use data on two proxies for global economic activity starting in February 1982 and ending in month t. We first rescale the two log growth rates, obtained from the shipping cost index and the global crude steel production data, so they all have variances equal to one over the given sample period and then perform PCA. The first PCA corresponding to month t is kept each time and the process is repeated using expanding windows until December 2015 is reached.

A.2 Evaluation of predictive ability

In this paper, we examine the ability of (i) oil price changes and (ii) the oil supply, global demand, and oil-specific demand shocks embedded in these changes to forecast MSCI index excess returns.

[17] We use the X-13 Toolbox for Matlab, written by Yvan Lengwiler, to perform seasonal filtering. The source codes are retrieved from `http://www.mathworks.com/matlabcentral/fileexchange/49120-x-13-toolbox-for-seasonal-filtering/content/x13tbx/x13.m`.

Following the literature, we employ linear predictive regressions of the type:

$$r^{\mathsf{e}}_{t+1} = \alpha + \boldsymbol{\beta}'\mathbf{x}_t + u_{t+1}, \tag{20}$$

where r^{e}_{t+1} is the MSCI index excess return, $\mathbf{x}_t = [x_{1,t} \ \cdots \ x_{n,t}]'$ is a vector of predictors, $\boldsymbol{\beta} = [\beta_1 \ \cdots \ \beta_n]'$ is the vector of predictive slope coefficients, and u_{t+1} is a zero-mean random disturbance. The predictor $\mathbf{x}_t$ could be a scalar $(n = 1)$, e.g., when we use a sole predictor such as oil price change, or a multidimensional vector $(n > 1)$, e.g., when we use multiple predictors such as the three different shocks and/or additional controls. In some instances, we also consider the i.i.d. model for r^{e}_{t+1} in which case the vectors $\boldsymbol{\beta}$ and $\mathbf{x}_t$ are null and equation (20) reduces to $r^{\mathsf{e}}_{t+1} = \alpha + u_{t+1}$. We evaluate predictive ability in terms of both statistical and economic significance.

The question we wish to address is whether $\mathbf{x}_t$ can forecast the MSCI index excess return r^{e}_{t+1}. Hence, we are interested in testing the null hypotheses $H_0 : \beta_i = 0$, for $i = 1, \ldots, n$. We evaluate the statistical significance of predictive ability of $\mathbf{x}_t$ using standard metrics. Specifically, we obtain two-sided p-values for the null hypotheses $H_0 : \beta_i = 0$, $i = 1, \ldots, n$ based on standard errors computed according to two well-established approaches: (i) the Newey and West (1987) method, where the optimal bandwidth is selected following the approach in Newey and West (1994), and (ii) the Hodrick (1992) method that imposes the no-predictability condition. Finally, we also report adjusted R-squares.

To gauge the economic significance of the predictive ability of $\mathbf{x}_t$, we consider a mean-variance investor who can invest in an MSCI index and the corresponding short-term Treasury Bill. The investor uses the regression model (20) to forecast MSCI index excess returns. An optimal trading strategy is then developed based on the resulting estimates of the conditional mean and variance of excess returns. We evaluate economic significance in terms of two commonly used metrics: (i) the certainty equivalent return (CER) and (ii) the Sharpe ratio (SR) of the associated optimal portfolio returns.

Following Campbell and Thompson (2008), we assume that the risk aversion coefficient of the mean-variance investor is $\gamma = 3$. At the end of each period t, the investor uses all available data to estimate the parameters of the linear predictive regression (20). Using these parameter estimates, the investor then obtains estimates of the mean and the variance of the MSCI index excess return r^{e}_{t+1} at time t, denoted by $\widehat{\mu}_{t+1}$ and $\widehat{v}_{t+1}$, respectively. These estimates give rise to the following optimal portfolio weight on the MSCI index:

$$\omega_t = \frac{1}{\gamma}\frac{\widehat{\mu}_{t+1}}{\widehat{v}_{t+1}}. \tag{21}$$

The rest of the investor's wealth is invested in the short-term Treasury Bill. We assume that the portfolio weight on the MSCI index is constrained between a minimum and maximum feasible weight, denoted by $\underline{\omega}$ and $\overline{\omega}$, respectively. The minimum weight $\underline{\omega}$ is set equal to zero so that short-selling is precluded. Following Campbell and Thompson (2008), we set the maximum weight, $\overline{\omega}$, equal to 150% so that the investor is allowed to borrow up to 50% and invest the proceeds in the MSCI index. Optimal weights are determined according to equation (21) and then the realized portfolio returns are computed. Below, we describe the two metrics, CER and SR, used in our evaluation of economic significance of predictability.

The CER of the resulting optimal portfolio from period 1 to period T based on the predictive regression (20) is given by

$$\widehat{\mathtt{CER}} \;=\; \widehat{\mu}_p \;-\frac{\gamma}{2}\widehat{v}_p, \tag{22}$$

where the mean $\widehat{\mu}_p$ and the variance $\widehat{v}_p$ of the realized optimal portfolio net returns are defined by

$$\widehat{\mu}_p = \frac{1}{T}\sum_{t=0}^{T-1}(r^{\mathsf{f}}_{t+1} + \omega_t r^{\mathsf{e}}_{t+1}) \quad \text{and} \quad \widehat{v}_p = \frac{1}{T}\sum_{t=0}^{T-1}\big((r^{\mathsf{f}}_{t+1} + \omega_t r^{\mathsf{e}}_{t+1}) - \widehat{\mu}_p\big)^2, \tag{23}$$

and r^{e}_{t+1} and r^{f}_{t+1} denote the excess return on the MSCI index and the corresponding Treasury Bill rate at time $t+1$, respectively.

The SR of the resulting optimal portfolio from period 1 to period T based on the predictive regression (20) is given by

$$\widehat{\mathtt{SR}} \;=\; \frac{\widehat{\mu}^{\mathsf{e}}_p}{\sqrt{\widehat{v}^{\mathsf{e}}_p}}, \tag{24}$$

with the mean and the variance of the realized optimal portfolio excess returns defined by

$$\widehat{\mu}_p^{\mathsf{e}} = \frac{1}{T}\sum_{t=0}^{T-1} \omega_t r_{t+1}^{\mathsf{e}} \quad \text{and} \quad \widehat{v}_p^{\mathsf{e}} = \frac{1}{T}\sum_{t=0}^{T-1} (\omega_t r_{t+1}^{\mathsf{e}} - \widehat{\mu}_p^{\mathsf{e}})^2. \tag{25}$$

We express the CERs obtained from equation (22) in annualized percentages by multiplying by 1,200 and annualize the monthly SRs from equation (24) by multiplying by $\sqrt{12}$. CER represents the equivalent risk-free rate of return that a mean-variance investor would require in exchange of a risky portfolio return series, while SR measures the average portfolio excess return per unit of risk as measured by the portfolio excess return standard deviation.

If the variables in a vector $\mathbf{x}_t$ have nontrivial predictive ability, then using the predictive regression model (20) is expected to generate a higher CER (SR) than using the i.i.d. model for the MSCI index excess returns r_{t+1}^{e}. In this context, we refer to the i.i.d. model as the baseline model (Model 1) and the predictive regression model using the vector of predictors $\mathbf{x}_t$ as the alternative model (Model 2). We are interested in providing a formal comparison of the two models in terms of CER and SR. Denote by $\mathtt{CER}_j$ and $\mathtt{SR}_j$ the CER and SR of Model j, for $j = 1, 2$. Even if the point estimate of the CER and/or SR generated by the alternative model is higher than its counterpart generated by the baseline model, i.e., $\widehat{\mathtt{CER}}_1 < \widehat{\mathtt{CER}}_2$, one might be concerned whether this is due to genuine predictive ability of $\mathbf{x}_t$ or simply due to sample variability. Therefore, it is important to test the statistical significance of any differences in CER and SR. To this end, we develop asymptotic tests for the null hypothesis $H_0^{\mathsf{CER}} : \mathtt{CER}_1 = \mathtt{CER}_2$ against the one-sided alternative $H_A^{\mathsf{CER}} : \mathtt{CER}_1 < \mathtt{CER}_2$ and similarly the null hypothesis $H_0^{\mathsf{SR}} : \mathtt{SR}_1 = \mathtt{SR}_2$ against the one-sided alternative $H_A^{\mathsf{SR}} : \mathtt{SR}_1 < \mathtt{SR}_2$. Our purpose is to evaluate the incremental value of the alternative Model 2 compared to the baseline Model 1 and, hence, we focus on one-sided alternative hypotheses. The same framework can be used to facilitate more general comparisons. For instance, an important comparison in terms of predictive ability is between the oil price change and the vector of oil supply, global demand, and oil-specific demand shocks. For this comparison, Model 1 (baseline) corresponds to the predictive regression (20) with $\mathbf{x}_t$ consisting of the oil price change, while Model 2 (alternative) corresponds to the predictive regression (20) with $\mathbf{x}_t$ consisting of the three shocks.

Next, we provide the details about the aforementioned asymptotic tests and the computation of p-values. Let $\mathbf{r}_t = (r_{1,t}, r_{2,t})'$ denote the pair of returns on the portfolios generated by Models 1 and 2 at time t. These returns would be either net or excess depending on whether we focus on the CER or the SR. Note that, in the context of our mean-variance framework, the CER of a portfolio is expressed as a function of the first two moments of net portfolio returns, while the SR of a portfolio is expressed as a function of the first two moments of the portfolio excess returns. Denote the mean, variance, and non-central second moment of $r_{j,t}$ by μ_j, σ_j^2, and ν_j, respectively for the portfolios $j = 1, 2$. Note that $\sigma_j^2 = \nu_j - \mu_j^2$. It follows that, in the case of net returns, the CERs for an investor with mean-variance preferences and a risk aversion coefficient equal to γ are given by $\texttt{CER}_j = \mu_j - \frac{\gamma}{2}\left(\nu_j - \mu_j^2\right)$, $j = 1, 2$. Similarly, in the case of excess returns, the SRs are given by $\texttt{SR}_j = \frac{\mu_j}{\sqrt{\nu_j - \mu_j^2}}$, $j = 1, 2$. Therefore, the relevant hypotheses can be stated using a suitable function of the parameter vector $\boldsymbol{\theta} = (\mu_1, \mu_2, \nu_1, \nu_2)'$. We estimate $\boldsymbol{\theta}$ by the sample analogue $\widehat{\boldsymbol{\theta}} = (\widehat{\mu}_1, \widehat{\mu}_2, \widehat{\nu}_1, \widehat{\nu}_2)'$, where $\widehat{\mu}_j = \frac{1}{T}\sum_{t=1}^T r_{j,t}$ and $\widehat{\nu}_j = \frac{1}{T}\sum_{t=1}^T r_{j,t}^2$, for $j = 1, 2$. Under regularity conditions, such as stationarity and ergodicity, $\widehat{\boldsymbol{\theta}}$ asymptotically follows a normal distribution described by

$$\sqrt{T}(\widehat{\boldsymbol{\theta}} - \boldsymbol{\theta}) = \frac{1}{\sqrt{T}}\sum\nolimits_{t=1}^{T} \mathbf{y}_t \xrightarrow{d} N(\mathbf{0}, \boldsymbol{\Psi}), \tag{26}$$

where $\boldsymbol{\Psi}$ is the long-run variance-covariance matrix of

$$\mathbf{y}_t = \left(r_{1,t} - \mu_1, r_{2,t} - \mu_2, r_{1,t}^2 - \nu_1, r_{2,t}^2 - \nu_2\right)'. \tag{27}$$

The matrix $\boldsymbol{\Psi}$ is given by $\boldsymbol{\Psi} = \boldsymbol{\Gamma}_0 + \sum_{\ell=1}^{\infty}(\boldsymbol{\Gamma}_\ell + \boldsymbol{\Gamma}_\ell')$, where $\boldsymbol{\Gamma}_\ell = \mathrm{E}\left[\mathbf{y}_t \mathbf{y}_{t-\ell}'\right]$, for $\ell = 0, 1, \ldots$ and is estimated by a heteroscedasticity and autocorrelation consistent (HAC) estimator of the form

$$\widehat{\boldsymbol{\Psi}} = \widehat{\boldsymbol{\Gamma}}_0 + \sum_{\ell=1}^{T} \kappa\left(\frac{\ell}{b_T}\right)(\widehat{\boldsymbol{\Gamma}}_\ell + \widehat{\boldsymbol{\Gamma}}_\ell'), \tag{28}$$

where

$$\widehat{\boldsymbol{\Gamma}}_\ell = \frac{1}{T-\ell}\sum_{t=\ell+1}^{T} \widehat{\mathbf{y}}_t \widehat{\mathbf{y}}_{t-\ell}', \quad \widehat{\mathbf{y}}_t = \left(r_{1,t} - \widehat{\mu}_1, r_{2,t} - \widehat{\mu}_2, r_{1,t}^2 - \widehat{\nu}_1, r_{2,t}^2 - \widehat{\nu}_2\right)', \tag{29}$$

$\kappa(\cdot)$ is a kernel function, and b_T is the bandwidth. HAC estimators have been developed by several authors including Newey and West (1987), Andrews (1991), Andrews and Monahan (1992), and Newey and West (1994). We report p-values based on the Newey and West (1987) approach with the Bartlett kernel and the optimal bandwidth computed as suggested in Newey and West (1994).

Consider testing the null hypothesis $H_0 : f(\boldsymbol{\theta}) = 0$ against the alternative hypothesis $H_A : f(\boldsymbol{\theta}) < 0$, where $f(\boldsymbol{\theta})$ is a smooth real-valued function of $\boldsymbol{\theta}$. Applying the delta method, we obtain

$$\sqrt{T}\left(f(\widehat{\boldsymbol{\theta}}) - f(\boldsymbol{\theta})\right) \xrightarrow{d} N\left(0, \nabla' f(\boldsymbol{\theta}) \boldsymbol{\Psi} \nabla f(\boldsymbol{\theta})\right), \tag{30}$$

where $\nabla f(\cdot)$ is the gradient of f. For large T, the standard error of $f(\widehat{\boldsymbol{\theta}})$ is given by

$$se(f(\widehat{\boldsymbol{\theta}})) = \sqrt{\frac{1}{T}\nabla' f(\widehat{\boldsymbol{\theta}}) \widehat{\boldsymbol{\Psi}} \nabla f(\widehat{\boldsymbol{\theta}})}, \tag{31}$$

and, therefore, the corresponding t-statistic is $t(f, \widehat{\boldsymbol{\theta}}) = \frac{f(\widehat{\boldsymbol{\theta}})}{se(f(\widehat{\boldsymbol{\theta}}))}$, yielding the one-sided p-value $p(f, \widehat{\boldsymbol{\theta}}) = \Phi(t(f, \widehat{\boldsymbol{\theta}}))$, where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution.

To test for equality of CERs, we use net returns and the function f takes the form

$$f_{\mathsf{CER}}(\boldsymbol{\theta}) = \left(\mu_1 - \frac{\gamma}{2}\left(\nu_1 - \mu_1^2\right)\right) - \left(\mu_2 - \frac{\gamma}{2}\left(\nu_2 - \mu_2^2\right)\right), \tag{32}$$

with gradient equal to

$$\nabla f_{\mathsf{CER}}(\boldsymbol{\theta}) = \left(1 + \gamma\mu_1, -1 - \gamma\mu_2, -\frac{\gamma}{2}, \frac{\gamma}{2}\right)'. \tag{33}$$

To test for equality of SRs, we use excess returns and the function f takes the form

$$f_{\mathsf{SR}}(\boldsymbol{\theta}) = \frac{\mu_1}{\sqrt{\nu_1 - \mu_1^2}} - \frac{\mu_2}{\sqrt{\nu_2 - \mu_2^2}}, \tag{34}$$

with gradient equal to

$$\nabla f_{\mathsf{SR}}(\boldsymbol{\theta}) = \left(\frac{\nu_1}{(\nu_1 - \mu_1^2)^{\frac{3}{2}}}, -\frac{\nu_2}{(\nu_2 - \mu_2^2)^{\frac{3}{2}}}, -\frac{1}{2}\frac{\mu_1}{(\nu_1 - \mu_1^2)^{\frac{3}{2}}}, \frac{1}{2}\frac{\mu_2}{(\nu_2 - \mu_2^2)^{\frac{3}{2}}}\right)'. \tag{35}$$

Table 1: **Oil price change summary statistics.** This table presents summary statistics for three oil spot price log growth rates, i.e., West Texas Intermediate (WTI), Dubai, and Arab Light, and their first principal component g^{P}. Results are presented for the 1983.01–2003.04 and the 1983.01–2015.12 sample periods. All reported numbers are in percentages.

1983.01–2003.04 Sample Period

	WTI	Dubai	Arab Light	g^{P}
Min	−39.60	−37.76	−48.51	−49.85
Max	37.71	53.68	48.73	38.16
Mean	−0.05	−0.10	−0.08	−0.26
Std. dev.	8.17	10.51	10.94	9.18
# of obs.	244	244	244	244

Correlation Matrix

	WTI	Dubai	Arab Light	g^{P}
WTI	1.00	0.76	0.72	0.90
Dubai	0.76	1.00	0.90	0.94
Arab Light	0.72	0.90	1.00	0.92
g^{P}	0.90	0.94	0.92	1.00

1983.01–2015.12 Sample Period

	WTI	Dubai	Arab Light	g^{P}
Min	−39.60	−49.71	−48.51	−49.85
Max	37.71	53.68	48.73	38.16
Mean	0.04	0.02	0.01	−0.09
Std. dev.	8.45	10.16	10.34	9.00
# of obs.	396	396	396	396

Correlation Matrix

	WTI	Dubai	Arab Light	g^{P}
WTI	1.00	0.76	0.72	0.90
Dubai	0.76	1.00	0.91	0.95
Arab Light	0.72	0.91	1.00	0.93
g^{P}	0.90	0.95	0.93	1.00

Table 2: **Oil price change as a predictor of MSCI index excess returns: statistical significance over the 1983.01–2003.04 and 1983.01–2015.12 sample periods.** This table presents in-sample statistical significance results for the predictive regression $r^{\mathsf{e}}_{t+1} = \alpha^{\mathsf{P}} + \delta^{\mathsf{P}} g^{\mathsf{P}}_t + u^{\mathsf{P}}_{t+1}$, where r^{e}_{t+1} is the excess return on an MSCI index and the oil price change proxy g^{P}_t is the first principal component obtained from three oil spot price log growth rates: West Texas Intermediate, Dubai, and Arab Light. The top and bottom panels contain results for local currency- and US dollar-denominated index returns, respectively. We report the two-sided p-values for the null hypotheses $H_0 : \delta^{\mathsf{P}} = 0$, denoted by NW[$p$] and H[$p$], based on Newey and West (1987) standard errors, with optimal bandwidth selected as in Newey and West (1994), and Hodrick (1992) standard errors, respectively. The adjusted R^2, presented as a percentage, is denoted by $\bar{R}^2$. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1983.01–2003.04				1983.01–2015.12			
	δ^{P}	NW[p]	H[p]	$\bar{R}^2$	δ^{P}	NW[p]	H[p]	$\bar{R}^2$
Local currency								
Canada	−0.06	0.06*	0.08*	1.0	−0.01	0.86	0.82	−0.2
France	−0.15	0.00***	0.01**	4.9	−0.08	0.08*	0.06*	1.4
Germany	−0.17	0.00***	0.01***	4.8	−0.08	0.11	0.10*	1.0
Italy	−0.32	0.00***	0.00***	16.4	−0.19	0.01***	0.00***	6.2
Japan	−0.11	0.07*	0.12	2.9	−0.05	0.29	0.34	0.3
UK	−0.11	0.00***	0.01***	4.1	−0.06	0.03**	0.03**	1.4
US dollar								
Canada	−0.06	0.09*	0.13	0.7	0.01	0.78	0.72	−0.2
France	−0.13	0.00***	0.02**	3.3	−0.06	0.31	0.22	0.4
Germany	−0.15	0.00***	0.02**	3.7	−0.06	0.24	0.24	0.4
Italy	−0.31	0.00***	0.00***	14.3	−0.17	0.01**	0.00***	4.1
Japan	−0.09	0.14	0.27	0.9	−0.04	0.34	0.42	0.1
UK	−0.10	0.00***	0.04**	2.3	−0.03	0.49	0.40	0.0
US	−0.12	0.00***	0.00***	5.2	−0.05	0.22	0.14	0.6
World	−0.12	0.00***	0.01***	5.6	−0.04	0.22	0.20	0.6

Table 3: **Bai-Perron structural break tests: oil price changes for the 1983.01–2015.12 sample period.** This table presents Bai and Perron (2003) structural break tests for the predictive regression $r^{\mathsf{e}}_{t+1} = \alpha^{\mathsf{P}} + \delta^{\mathsf{P}} g^{\mathsf{P}}_t + u^{\mathsf{P}}_{t+1}$, where r^{e}_{t+1} is excess return on an MSCI index and the oil price change proxy g^{P}_t is the first principal component obtained from three oil spot price log growth rates: West Texas Intermediate, Dubai, and Arab Light. The top and bottom panels contain results for local currency- and US dollar-denominated index returns, respectively. Bold numbers indicate the lowest value assumed by the Bayesian Information Criterion (BIC).

	No break model	One break model		# of breaks
	BIC	BIC	Break date	selected by BIC
Local currency				
Canada	−6.281	**−6.283**	2008.08	1
France	−5.789	**−5.790**	2008.08	1
Germany	−5.588	**−5.592**	2008.07	1
Italy	−5.514	**−5.554**	2003.10	1
Japan	−5.760	**−5.763**	1990.09	1
UK	**−6.232**	−6.228	2008.08	0
US dollar				
Canada	−5.810	**−5.815**	2008.07	1
France	**−5.601**	−5.598	2008.07	0
Germany	−5.419	**−5.421**	2008.07	1
Italy	−5.301	**−5.335**	2003.10	1
Japan	−5.570	**−5.575**	1990.09	1
UK	−5.929	**−5.933**	2008.07	1
US	−6.290	**−6.318**	2008.08	1
World	−6.283	**−6.308**	2008.07	1

Table 4: **Oil supply, global demand, and oil-specific demand shocks, based on the IS model, as predictors of MSCI index excess returns: statistical significance results, based on Newey and West (1987) standard errors, over the 1986.01–2015.12 sample period.** The left panel presents in-sample results for the predictive regression $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{P}} + \delta^{\mathtt{P}} g^{\mathtt{P}}_t + u^{\mathtt{P}}_{t+1}$, where $r^{\mathtt{e}}_{t+1}$ is excess return on an MSCI index and the oil price change proxy $g^{\mathtt{P}}_t$ is the first principal component obtained from three oil spot price log growth rates: West Texas Intermediate, Dubai, and Arab Light. The right panel presents in-sample results for the predictive regression $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{DEC}} + \beta^{\mathtt{S}} x^{\mathtt{S}}_t + \beta^{\mathtt{GD}} x^{\mathtt{GD}}_t + \beta^{\mathtt{OSD}} x^{\mathtt{OSD}}_t + u^{\mathtt{DEC}}_{t+1}$, where $x^{\mathtt{S}}_t$, $x^{\mathtt{GD}}_t$, and $x^{\mathtt{OSD}}_t$ are the oil supply, global demand, and oil-specific demand shocks obtained in the oil price change decomposition (8). Shown are the estimates of the predictive slope coefficients $\delta^{\mathtt{P}}$ (left panel) and β^i, $i = \mathtt{S}, \mathtt{GD}, \mathtt{OSD}$ (right panel), as well as two-sided p-values for the null hypotheses that the slope coefficients are zero, denoted by NW[p], based on Newey and West (1987) standard errors with optimal bandwidth selected as in Newey and West (1994). The top and bottom panels contain results for local currency- and US dollar-denominated index returns, respectively. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The adjusted R^2, presented as a percentage, is denoted by $\bar{R}^2$.

	Oil Price Change			IS Model OPC Decomposition						
	$\delta^{\mathtt{P}}$	NW[p]	$\bar{R}^2$	$\beta^{\mathtt{S}}$	NW[p]	$\beta^{\mathtt{GD}}$	NW[p]	$\beta^{\mathtt{OSD}}$	NW[p]	$\bar{R}^2$
Local currency										
Canada	−0.00	0.91	−0.3	−0.18	0.60	0.27	0.01***	−0.03	0.39	1.5
France	−0.08	0.09*	1.5	−0.43	0.39	0.23	0.06*	−0.10	0.01**	2.9
Germany	−0.08	0.12	1.0	−0.50	0.39	0.31	0.02**	−0.11	0.01**	3.1
Italy	−0.18	0.01**	6.2	−0.75	0.07*	0.32	0.03**	−0.22	0.00***	9.5
Japan	−0.05	0.32	0.3	0.21	0.56	0.31	0.00***	−0.08	0.06*	1.9
UK	−0.06	0.03**	1.4	0.17	0.70	0.16	0.13	−0.09	0.00***	2.3
US dollar										
Canada	0.02	0.74	−0.2	−0.26	0.56	0.35	0.01***	−0.01	0.82	1.5
France	−0.06	0.30	0.4	−0.57	0.21	0.23	0.24	−0.07	0.08*	1.5
Germany	−0.06	0.26	0.3	−0.66	0.20	0.30	0.10*	−0.08	0.04**	1.9
Italy	−0.16	0.02**	4.1	−0.91	0.07*	0.32	0.12	−0.20	0.00***	6.6
Japan	−0.04	0.37	0.1	0.61	0.18	0.19	0.06*	−0.07	0.11	0.7
UK	−0.03	0.49	0.0	0.01	0.98	0.32	0.05**	−0.06	0.04**	2.1
US	−0.04	0.27	0.5	−0.36	0.36	0.32	0.00***	−0.07	0.01**	4.3
World	−0.04	0.26	0.5	−0.19	0.58	0.31	0.01**	−0.07	0.02**	3.6

Table 5: **Oil supply, global demand, and oil-specific demand shocks, based on the ES model, as predictors of MSCI index excess returns: statistical significance results, based on Newey and West (1987) standard errors, over the 1986.01–2015.12 sample period.** The left panel presents in-sample results for the predictive regression $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{P}} + \delta^{\mathtt{P}} g^{\mathtt{P}}_t + u^{\mathtt{P}}_{t+1}$, where $r^{\mathtt{e}}_{t+1}$ is excess return on an MSCI index and the oil price change proxy $g^{\mathtt{P}}_t$ is the first principal component obtained from three oil spot price log growth rates: West Texas Intermediate, Dubai, and Arab Light. The right panel presents in-sample results for the predictive regression $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{DEC}} + \beta^{\mathtt{S}} x^{\mathtt{S}}_t + \beta^{\mathtt{GD}} x^{\mathtt{GD}}_t + \beta^{\mathtt{OSD}} x^{\mathtt{OSD}}_t + u^{\mathtt{DEC}}_{t+1}$, where $x^{\mathtt{S}}_t$, $x^{\mathtt{GD}}_t$, and $x^{\mathtt{OSD}}_t$ are the oil supply, global demand, and oil-specific demand shocks obtained in the oil price change decomposition (8). Shown are the estimates of the predictive slope coefficients $\delta^{\mathtt{P}}$ (left panel) and β^i, $i = \mathtt{S}, \mathtt{GD}, \mathtt{OSD}$ (right panel), as well as two-sided p-values for the null hypotheses that the slope coefficients are zero, denoted by NW[p], based on Newey and West (1987) standard errors with optimal bandwidth selected as in Newey and West (1994). The top and bottom panels contain results for local currency- and US dollar-denominated index returns, respectively. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The adjusted R^2, presented as a percentage, is denoted by $\bar{R}^2$.

	Oil Price Change			ES Model OPC Decomposition						
	$\delta^{\mathtt{P}}$	NW[p]	$\bar{R}^2$	$\beta^{\mathtt{S}}$	NW[p]	$\beta^{\mathtt{GD}}$	NW[p]	$\beta^{\mathtt{OSD}}$	NW[p]	$\bar{R}^2$
Local currency										
Canada	−0.00	0.91	−0.3	−0.05	0.30	0.30	0.02**	−0.00	0.98	1.5
France	−0.08	0.09*	1.5	−0.18	0.00***	0.31	0.08*	−0.00	1.00	3.3
Germany	−0.08	0.12	1.0	−0.18	0.01**	0.40	0.01**	−0.01	0.88	3.2
Italy	−0.18	0.01**	6.2	−0.25	0.00***	0.39	0.06*	−0.18	0.14	9.0
Japan	−0.05	0.32	0.3	−0.16	0.04**	0.43	0.00***	0.04	0.64	3.1
UK	−0.06	0.03**	1.4	−0.15	0.00***	0.23	0.07*	0.02	0.72	3.2
US dollar										
Canada	0.02	0.74	−0.2	−0.04	0.44	0.40	0.02**	0.03	0.72	1.5
France	−0.06	0.30	0.4	−0.11	0.11	0.28	0.24	−0.03	0.77	1.1
Germany	−0.06	0.26	0.3	−0.12	0.12	0.35	0.09*	−0.04	0.69	1.5
Italy	−0.16	0.02**	4.1	−0.19	0.01***	0.36	0.12	−0.21	0.11	6.0
Japan	−0.04	0.37	0.1	−0.12	0.16	0.26	0.01***	0.02	0.81	0.7
UK	−0.03	0.49	0.0	−0.11	0.03**	0.37	0.07*	0.01	0.85	2.3
US	−0.04	0.27	0.5	−0.10	0.01***	0.38	0.01***	−0.03	0.55	4.2
World	−0.04	0.26	0.5	−0.12	0.03**	0.38	0.01**	−0.01	0.88	4.1

Table 6: **Oil supply, global demand, and oil-specific demand shocks, based on the IS model, as predictors of MSCI index excess returns: economic significance over the 1986.01–2015.12 sample period.** This table presents evidence on the performance of the optimal trading strategies using oil supply, global demand, and oil-specific demand shocks as predictors in terms of two metrics: the certainty equivalent return (CER) and the Sharpe ratio (SR). The investor forms optimal mean-variance portfolios between an MSCI index and the corresponding Treasury Bill and has a risk aversion coefficient $\gamma = 3$. The weight on the MSCI index is constrained between $\underline{\omega} = 0$ and $\overline{\omega} = 150\%$. We compare the alternative model (`DEC-IS`) described by the predictive regression $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{DEC}} + \beta^{\mathtt{S}} x^{\mathtt{S}}_t + \beta^{\mathtt{GD}} x^{\mathtt{GD}}_t + \beta^{\mathtt{OSD}} x^{\mathtt{OSD}}_t + u^{\mathtt{DEC}}_{t+1}$, where $x^{\mathtt{S}}_t$, $x^{\mathtt{GD}}_t$, and $x^{\mathtt{OSD}}_t$ are the oil supply, global demand, and oil-specific demand shocks obtained in the oil price change decomposition (8) to three baseline models. The first baseline model (`IID`) assumes that the MSCI index excess return $r^{\mathtt{e}}_{t+1}$ is i.i.d. The second baseline model (`P`) is described by the predictive regression $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{P}} + \delta^{\mathtt{P}} g^{\mathtt{P}}_t + u^{\mathtt{P}}_{t+1}$, where the oil price change proxy $g^{\mathtt{P}}_t$ is the first principal component obtained from three oil spot price log growth rates: West Texas Intermediate, Dubai, and Arab Light. The third baseline model (`GD`) is described by the predictive regression $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{GD}} + \delta^{\mathtt{GD}} g^{\mathtt{GD}}_t + u^{\mathtt{GD}}_{t+1}$, where the global demand growth proxy $g^{\mathtt{GD}}_t$ is the first principal component obtained from the log growth rates of shipping cost index and global crude steel production. The portfolio strategies use the mean and variance estimates resulting from each model respectively. Reported are the CERs in annualized percentage points and the annualized SRs for the alternative and the three baseline models. We also report the one-sided p-values for the null hypothesis that the alternative model does not improve the CER and SR obtained from the optimal trading strategies based on each of the three baseline models. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The top and bottom panels contain results for local currency- and US dollar-denominated index returns, respectively. The results are based on an expanding window with 60 initial observations.

	CER							SR						
	`DEC-IS`	`IID`	p-value	`P`	p-value	`GD`	p-value	`DEC-IS`	`IID`	p-value	`P`	p-value	`GD`	p-value
Local currency														
Canada	6.68	4.40	0.09*	4.90	0.17	5.62	0.26	0.45	0.25	0.10	0.31	0.22	0.37	0.27
France	6.03	4.24	0.24	6.10	0.51	2.93	0.11	0.41	0.23	0.14	0.41	0.49	0.18	0.08*
Germany	7.44	3.58	0.08*	5.77	0.23	3.78	0.09*	0.51	0.17	0.03**	0.40	0.18	0.24	0.06*
Italy	10.70	4.32	0.03**	8.73	0.12	3.04	0.01***	0.61	−0.06	0.00***	0.50	0.13	0.00	0.00***
Japan	3.56	−0.20	0.05**	−1.67	0.07*	−1.37	0.01**	0.42	−0.11	0.00***	0.02	0.02**	−0.14	0.00***
UK	8.52	4.74	0.04**	7.32	0.25	3.94	0.03**	0.53	0.19	0.02**	0.45	0.28	0.13	0.02**
US dollar														
Canada	4.06	3.31	0.37	1.96	0.25	4.12	0.51	0.34	0.26	0.30	0.19	0.23	0.34	0.48
France	0.90	3.46	0.81	2.48	0.76	1.82	0.63	0.22	0.26	0.64	0.25	0.63	0.20	0.47
Germany	3.50	3.27	0.47	2.37	0.37	3.29	0.47	0.33	0.21	0.20	0.25	0.27	0.26	0.33
Italy	5.30	2.27	0.19	3.20	0.27	0.48	0.10*	0.44	0.05	0.01***	0.34	0.23	0.05	0.02**
Japan	4.11	1.46	0.04**	0.60	0.02**	−0.69	0.01***	0.30	−0.11	0.00***	−0.05	0.00***	−0.26	0.00***
UK	5.33	3.38	0.19	2.74	0.21	2.67	0.12	0.41	0.25	0.12	0.23	0.18	0.22	0.08*
US	9.28	6.52	0.11	6.08	0.08*	6.20	0.05**	0.65	0.48	0.12	0.45	0.09*	0.46	0.05**
World	7.90	4.03	0.04**	3.88	0.07*	3.30	0.03**	0.56	0.31	0.04**	0.30	0.06*	0.27	0.03**

Table 7: **Oil supply, global demand, and oil-specific demand shocks, based on the ES model, as predictors of MSCI index excess returns: economic significance over the 1986.01–2015.12 sample period.** This table presents evidence on the performance of the optimal trading strategies using oil supply, global demand, and oil-specific demand shocks as predictors in terms of two metrics: the certainty equivalent return (CER) and the Sharpe ratio (SR). The investor forms optimal mean-variance portfolios between an MSCI index and the corresponding Treasury Bill and has a risk aversion coefficient $\gamma = 3$. The weight on the MSCI index is constrained between $\underline{\omega} = 0$ and $\overline{\omega} = 150\%$. We compare the alternative model (DEC-ES) described by the predictive regression $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{DEC}} + \beta^{\mathtt{S}} x^{\mathtt{S}}_t + \beta^{\mathtt{GD}} x^{\mathtt{GD}}_t + \beta^{\mathtt{OSD}} x^{\mathtt{OSD}}_t + u^{\mathtt{DEC}}_{t+1}$, where $x^{\mathtt{S}}_t$, $x^{\mathtt{GD}}_t$, and $x^{\mathtt{OSD}}_t$ are the oil supply, global demand, and oil-specific demand shocks obtained in the oil price change decomposition (8) to three baseline models. The first baseline model (IID) assumes that the MSCI index excess return $r^{\mathtt{e}}_{t+1}$ is i.i.d. The second baseline model (P) is described by the predictive regression $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{P}} + \delta^{\mathtt{P}} g^{\mathtt{P}}_t + u^{\mathtt{P}}_{t+1}$, where the oil price change proxy $g^{\mathtt{P}}_t$ is the first principal component obtained from three oil spot price log growth rates: West Texas Intermediate, Dubai, and Arab Light. The third baseline model (GD) is described by the predictive regression $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{GD}} + \delta^{\mathtt{GD}} g^{\mathtt{GD}}_t + u^{\mathtt{GD}}_{t+1}$, where the global demand growth proxy $g^{\mathtt{GD}}_t$ is the first principal component obtained from the log growth rates of shipping cost index and global crude steel production. The portfolio strategies use the mean and variance estimates resulting from each model respectively. Reported are the CERs in annualized percentage points and the annualized SRs for the alternative and the three baseline models. We also report the one-sided p-values for the null hypothesis that the alternative model does not improve the CER and SR obtained from the optimal trading strategies based on each of the three baseline models. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The top and bottom panels contain results for local currency- and US dollar-denominated index returns, respectively. The results are based on an expanding window with 60 initial observations.

	CER							SR						
	DEC-ES	IID	p-value	P	p-value	GD	p-value	DEC-ES	IID	p-value	P	p-value	GD	p-value
Local currency														
Canada	7.05	4.40	0.06*	4.90	0.15	5.62	0.21	0.48	0.25	0.08*	0.31	0.18	0.37	0.22
France	6.00	4.24	0.25	6.10	0.52	2.93	0.11	0.41	0.23	0.13	0.41	0.49	0.18	0.08*
Germany	7.56	3.58	0.10*	5.77	0.22	3.78	0.08*	0.52	0.17	0.02**	0.40	0.21	0.24	0.05*
Italy	10.47	4.32	0.04**	8.73	0.12	3.04	0.01***	0.59	−0.06	0.00***	0.50	0.14	0.00	0.00***
Japan	1.92	−0.20	0.14	−1.67	0.16	−1.37	0.04**	0.30	−0.11	0.00***	0.02	0.09*	−0.14	0.00***
UK	9.14	4.74	0.00***	7.32	0.15	3.94	0.01***	0.59	0.19	0.00***	0.45	0.16	0.13	0.00***
US dollar														
Canada	4.30	3.31	0.34	1.96	0.24	4.12	0.47	0.36	0.26	0.28	0.19	0.20	0.34	0.44
France	1.61	3.46	0.74	2.48	0.63	1.82	0.53	0.25	0.26	0.55	0.25	0.52	0.20	0.38
Germany	4.55	3.27	0.32	2.37	0.27	3.29	0.32	0.38	0.21	0.13	0.25	0.20	0.26	0.23
Italy	5.18	2.27	0.20	3.20	0.24	0.48	0.11	0.44	0.05	0.01***	0.34	0.19	0.05	0.02**
Japan	1.85	1.46	0.39	0.60	0.26	−0.69	0.07*	0.09	−0.11	0.09*	−0.05	0.18	−0.26	0.02**
UK	5.84	3.38	0.14	2.74	0.19	2.67	0.07*	0.44	0.25	0.08*	0.23	0.14	0.22	0.06*
US	9.78	6.52	0.07*	6.08	0.05*	6.20	0.02**	0.68	0.48	0.07*	0.45	0.06*	0.46	0.02**
World	7.67	4.03	0.05*	3.88	0.09*	3.30	0.03**	0.55	0.31	0.05**	0.30	0.06*	0.27	0.02**

Table 8: **Bai-Perron structural break tests: oil supply, global demand, and oil-specific demand shocks, based on the IS and ES models, as predictors of MSCI index returns for the 1986.01–2015.12 sample period.** This table presents Bai and Perron (2003) structural break tests for the predictive regression $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{DEC}} + \beta^{\mathtt{S}} x^{\mathtt{S}}_t + \beta^{\mathtt{GD}} x^{\mathtt{GD}}_t + \beta^{\mathtt{OSD}} x^{\mathtt{OSD}}_t + u^{\mathtt{DEC}}_{t+1}$, where $r^{\mathtt{e}}_{t+1}$ is excess return on an MSCI index and $x^{\mathtt{S}}_t$, $x^{\mathtt{GD}}_t$, $x^{\mathtt{OSD}}_t$ are the oil supply, global demand, oil-specific demand shocks obtained in the oil price change decomposition (8), respectively. The top and bottom panels contain results for local currency- and US dollar-denominated index returns, respectively. Bold numbers indicate the lowest value assumed by the Bayesian Information Criterion (BIC).

	IS Model				ES Model			
	No break model	One break model		# of breaks	No break model	One break model		# of breaks
	BIC	BIC	Break date	selected by BIC	BIC	BIC	Break date	selected by BIC
Local currency								
Canada	**−6.298**	−6.257	1994.02	0	**−6.297**	−6.259	2008.08	0
France	**−5.794**	−5.774	1995.03	0	**−5.799**	−5.774	1998.09	0
Germany	**−5.598**	−5.573	1994.06	0	**−5.600**	−5.574	1999.03	0
Italy	**−5.537**	−5.534	1994.06	0	−5.532	**−5.544**	1995.10	1
Japan	**−5.737**	−5.703	1990.09	0	**−5.749**	−5.712	1990.09	0
UK	**−6.240**	−6.197	2008.08	0	**−6.250**	−6.209	2010.03	0
US dollar								
Canada	**−5.803**	−5.765	2008.07	0	**−5.803**	−5.766	2008.07	0
France	**−5.597**	−5.561	1999.02	0	**−5.593**	−5.566	2010.03	0
Germany	**−5.436**	−5.407	1999.03	0	**−5.432**	−5.402	1999.03	0
Italy	**−5.313**	−5.296	1990.09	0	−5.306	**−5.306**	1990.09	1
Japan	**−5.551**	−5.531	1990.09	0	**−5.551**	−5.522	1990.09	0
UK	**−5.976**	−5.944	2010.01	0	**−5.978**	−5.951	2010.03	0
US	**−6.299**	−6.270	2008.08	0	**−6.298**	−6.268	2008.08	0
World	**−6.276**	−6.249	2008.07	0	**−6.281**	−6.258	2010.03	0

Table 9: **Oil supply, global demand, and oil-specific demand shocks, based on the IS model, as predictors of delayed monthly MSCI index returns: statistical significance over the 1986.01–2015.12 sample period.** This table presents results for the predictive regression $r^{\mathtt{d}}_{t+1} = \alpha^{\mathtt{DEC}} + \beta^{\mathtt{S}} x^{\mathtt{S}}_t + \beta^{\mathtt{GD}} x^{\mathtt{GD}}_t + \beta^{\mathtt{OSD}} x^{\mathtt{OSD}}_t + u^{\mathtt{DEC}}_{t+1}$, where $r^{\mathtt{d}}_{t+1}$ is the delayed monthly return on an MSCI index and $x^{\mathtt{S}}_t$, $x^{\mathtt{GD}}_t$, and $x^{\mathtt{OSD}}_t$ are the oil supply, global demand, and oil-specific demand shocks obtained in the oil price change decomposition (8). Shown are the estimates of the predictive slope coefficients β^i, $i = \mathtt{S}, \mathtt{GD}, \mathtt{OSD}$, as well as two-sided p-values for the null hypotheses that the slope coefficients are zero, denoted by NW[p], based on Newey and West (1987) standard errors with optimal bandwidth selected as in Newey and West (1994). Results based on a one-week and two-week delay are presented in the left and right panel, respectively. The top and bottom panels contain results for local currency- and US dollar-denominated index returns, respectively. The adjusted R^2, presented as a percentage, is denoted by $\bar{R}^2$. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	One-week delay							Two-week delay						
	$\beta^{\mathtt{S}}$	NW[p]	$\beta^{\mathtt{GD}}$	NW[p]	$\beta^{\mathtt{OSD}}$	NW[p]	$\bar{R}^2$	$\beta^{\mathtt{S}}$	NW[p]	$\beta^{\mathtt{GD}}$	NW[p]	$\beta^{\mathtt{OSD}}$	NW[p]	$\bar{R}^2$
Local currency														
Canada	−0.21	0.55	0.29	0.00***	−0.04	0.22	1.7	−0.14	0.68	0.30	0.00***	−0.03	0.35	1.7
France	0.01	0.98	0.27	0.06*	−0.12	0.00***	2.7	−0.16	0.69	0.26	0.01**	−0.09	0.02**	2.2
Germany	−0.18	0.76	0.35	0.05*	−0.13	0.00***	3.2	−0.50	0.32	0.37	0.00***	−0.11	0.00***	3.7
Italy	−0.36	0.44	0.47	0.00***	−0.21	0.00***	7.7	−0.30	0.56	0.50	0.00***	−0.19	0.00***	7.0
Japan	−0.09	0.81	0.37	0.00***	−0.08	0.02**	2.5	−0.13	0.76	0.40	0.00***	−0.08	0.02**	2.6
UK	0.39	0.50	0.24	0.02**	−0.09	0.00***	2.4	0.27	0.56	0.24	0.02**	−0.07	0.02**	1.8
US dollar														
Canada	−0.29	0.52	0.40	0.01***	−0.02	0.68	1.8	−0.28	0.51	0.41	0.00***	−0.01	0.83	2.3
France	0.03	0.95	0.32	0.02**	−0.08	0.01***	1.3	0.05	0.91	0.35	0.01***	−0.06	0.09*	1.6
Germany	−0.16	0.75	0.40	0.01***	−0.10	0.00***	2.2	−0.28	0.55	0.46	0.00***	−0.09	0.01***	3.3
Italy	−0.35	0.47	0.51	0.00***	−0.19	0.00***	5.5	−0.02	0.97	0.59	0.00***	−0.18	0.00***	5.6
Japan	0.19	0.71	0.27	0.02**	−0.08	0.02**	1.1	0.20	0.70	0.37	0.00***	−0.09	0.01***	2.0
UK	0.33	0.54	0.39	0.00***	−0.07	0.04**	2.4	0.40	0.36	0.41	0.00***	−0.06	0.04**	3.2
US	−0.04	0.92	0.34	0.00***	−0.07	0.01***	3.2	0.09	0.79	0.34	0.00***	−0.03	0.23	2.6
World	−0.06	0.86	0.37	0.00***	−0.07	0.00***	3.8	0.03	0.91	0.38	0.00***	−0.06	0.02**	4.0

Table 10: **Oil supply, global demand, and oil-specific demand shocks, based on the ES model, as predictors of delayed monthly MSCI index returns: statistical significance over the 1986.01–2015.12 sample period.** This table presents results for the predictive regression $r^{\mathtt{d}}_{t+1} = \alpha^{\mathtt{DEC}} + \beta^{\mathtt{S}} x^{\mathtt{S}}_t + \beta^{\mathtt{GD}} x^{\mathtt{GD}}_t + \beta^{\mathtt{OSD}} x^{\mathtt{OSD}}_t + u^{\mathtt{DEC}}_{t+1}$, where $r^{\mathtt{d}}_{t+1}$ is the delayed monthly return on an MSCI index and $x^{\mathtt{S}}_t$, $x^{\mathtt{GD}}_t$, and $x^{\mathtt{OSD}}_t$ are the oil supply, global demand, and oil-specific demand shocks obtained in the oil price change decomposition (8). Shown are the estimates of the predictive slope coefficients β^i, $i =$ S, GD, OSD, as well as two-sided p-values for the null hypotheses that the slope coefficients are zero, denoted by NW[p], based on Newey and West (1987) standard errors with optimal bandwidth selected as in Newey and West (1994). Results based on a one-week and two-week delay are presented in the left and right panel, respectively. The top and bottom panels contain results for local currency- and US dollar-denominated index returns, respectively. The adjusted R^2, presented as a percentage, is denoted by $\bar{R}^2$. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	One-week delay							Two-week delay						
	$\beta^{\mathtt{S}}$	NW[p]	$\beta^{\mathtt{GD}}$	NW[p]	$\beta^{\mathtt{OSD}}$	NW[p]	$\bar{R}^2$	$\beta^{\mathtt{S}}$	NW[p]	$\beta^{\mathtt{GD}}$	NW[p]	$\beta^{\mathtt{OSD}}$	NW[p]	$\bar{R}^2$
Local currency														
Canada	−0.06	0.14	0.33	0.00***	−0.01	0.85	1.6	−0.09	0.04**	0.37	0.00***	0.06	0.37	2.4
France	−0.21	0.00***	0.36	0.04**	0.01	0.85	3.5	−0.20	0.00***	0.37	0.01***	0.07	0.35	3.7
Germany	−0.21	0.00***	0.44	0.00***	−0.01	0.92	3.7	−0.20	0.00***	0.48	0.00***	0.01	0.92	4.4
Italy	−0.25	0.00***	0.55	0.02**	−0.15	0.11	7.8	−0.27	0.00***	0.65	0.00***	−0.07	0.44	8.0
Japan	−0.11	0.05**	0.42	0.00***	−0.04	0.54	2.6	−0.13	0.02**	0.48	0.00***	−0.00	0.96	2.9
UK	−0.13	0.00***	0.30	0.00***	−0.01	0.86	2.5	−0.10	0.06*	0.28	0.00***	0.00	1.00	1.8
US dollar														
Canada	−0.03	0.59	0.44	0.00***	−0.01	0.90	1.7	−0.08	0.13	0.50	0.00***	0.09	0.27	2.9
France	−0.14	0.05**	0.38	0.02**	0.00	0.97	1.6	−0.18	0.01***	0.48	0.00***	0.10	0.21	3.3
Germany	−0.14	0.07*	0.46	0.01***	−0.03	0.75	2.3	−0.18	0.01**	0.60	0.00***	0.04	0.67	4.4
Italy	−0.19	0.00***	0.56	0.01***	−0.18	0.11	5.5	−0.27	0.00***	0.77	0.00***	−0.04	0.67	6.9
Japan	−0.06	0.31	0.27	0.01**	−0.08	0.19	1.0	−0.09	0.15	0.40	0.00***	−0.07	0.34	2.0
UK	−0.08	0.20	0.43	0.00***	−0.03	0.69	2.4	−0.10	0.17	0.46	0.00***	0.01	0.92	3.1
US	−0.14	0.01***	0.42	0.00***	0.02	0.70	3.9	−0.13	0.02**	0.44	0.00***	0.11	0.09*	4.8
World	−0.12	0.01**	0.43	0.00***	−0.01	0.86	4.1	−0.14	0.01***	0.49	0.00***	0.07	0.32	5.8

Table 11: **Oil supply, global demand, and oil-specific demand shocks, based on the IS model, as predictors of long-horizon MSCI index returns: statistical significance over the 1986.01–2015.12 sample period.** This table presents results for the predictive regression $r_{t,t+h} = \alpha^{\mathtt{DEC}} + \beta^{\mathtt{S}} x_t^{\mathtt{S}} + \beta^{\mathtt{GD}} x_t^{\mathtt{GD}} + \beta^{\mathtt{OSD}} x_t^{\mathtt{OSD}} + u_{t+h}^{\mathtt{DEC}}$, where $r_{t,t+h}$ is the h-month return on an MSCI index and $x_t^{\mathtt{S}}$, $x_t^{\mathtt{GD}}$, and $x_t^{\mathtt{OSD}}$ are the oil supply, global demand, and oil-specific demand shocks obtained in the oil price change decomposition (8). Shown are the estimates of the predictive slope coefficients β^i, $i = \mathtt{S}$, $\mathtt{GD}$, $\mathtt{OSD}$, as well as two-sided p-values for the null hypotheses that the slope coefficients are zero, denoted by NW[p], based on Newey and West (1987) standard errors with optimal bandwidth selected as in Newey and West (1994). Results based on three-month and six-month returns are presented in the left and right panel, respectively. The top and bottom panels contain results for local currency- and US dollar-denominated index returns, respectively. The adjusted R^2, presented as a percentage, is denoted by $\bar{R}^2$. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Three-month return							Six-month return						
	$\beta^{\mathtt{S}}$	NW[p]	$\beta^{\mathtt{GD}}$	NW[p]	$\beta^{\mathtt{OSD}}$	NW[p]	$\bar{R}^2$	$\beta^{\mathtt{S}}$	NW[p]	$\beta^{\mathtt{GD}}$	NW[p]	$\beta^{\mathtt{OSD}}$	NW[p]	$\bar{R}^2$
Local currency														
Canada	−0.79	0.21	0.67	0.00***	0.01	0.80	3.4	−1.17	0.24	0.45	0.11	0.03	0.70	0.5
France	−1.18	0.12	0.76	0.05**	−0.11	0.11	4.0	−1.58	0.25	0.72	0.07*	−0.19	0.06*	2.3
Germany	−1.53	0.09*	0.92	0.01***	−0.09	0.19	4.6	−1.29	0.40	0.72	0.08*	−0.17	0.08*	1.4
Italy	−2.22	0.01***	1.04	0.00***	−0.29	0.00***	10.9	−1.97	0.13	0.92	0.02**	−0.36	0.00***	5.2
Japan	−0.97	0.26	0.63	0.01***	−0.11	0.15	2.3	−1.98	0.14	0.34	0.26	−0.25	0.06*	2.0
UK	−0.19	0.77	0.48	0.06*	−0.04	0.30	1.4	−0.09	0.93	0.59	0.06*	−0.05	0.53	0.7
US dollar														
Canada	−0.80	0.31	0.89	0.01***	0.05	0.52	3.7	−1.29	0.28	0.56	0.22	0.06	0.52	0.4
France	−1.46	0.11	0.92	0.02**	−0.01	0.88	4.6	−2.10	0.14	0.72	0.10	−0.13	0.24	2.1
Germany	−1.84	0.05**	1.10	0.00***	0.00	0.99	5.7	−1.75	0.19	0.72	0.11	−0.13	0.15	1.3
Italy	−2.45	0.01**	1.21	0.00***	−0.20	0.04**	9.0	−2.77	0.03**	0.91	0.06*	−0.33	0.03**	4.9
Japan	−0.32	0.79	0.71	0.00***	−0.10	0.27	1.7	−1.71	0.31	0.66	0.03**	−0.26	0.19	2.1
UK	−0.25	0.75	0.95	0.00***	−0.01	0.89	5.1	−0.67	0.53	0.87	0.02**	−0.03	0.73	1.7
US	−0.38	0.57	0.79	0.01***	−0.02	0.62	4.9	−1.02	0.27	0.72	0.02**	−0.03	0.71	1.9
World	−0.66	0.33	0.89	0.00***	−0.05	0.33	6.5	−1.25	0.22	0.78	0.02**	−0.12	0.17	3.0

Table 12: **Oil supply, global demand, and oil-specific demand shocks, based on the ES model, as predictors of long-horizon MSCI index returns: statistical significance over the 1986.01–2015.12 sample period.** This table presents results for the predictive regression $r_{t,t+h} = \alpha^{\mathtt{DEC}} + \beta^{\mathtt{S}} x_t^{\mathtt{S}} + \beta^{\mathtt{GD}} x_t^{\mathtt{GD}} + \beta^{\mathtt{OSD}} x_t^{\mathtt{OSD}} + u_{t+h}^{\mathtt{DEC}}$, where $r_{t,t+h}$ is the h-month return on an MSCI index and $x_t^{\mathtt{S}}$, $x_t^{\mathtt{GD}}$, and $x_t^{\mathtt{OSD}}$ are the oil supply, global demand, and oil-specific demand shocks obtained in the oil price change decomposition (8). Shown are the estimates of the predictive slope coefficients β^i, $i = \mathtt{S}$, $\mathtt{GD}$, $\mathtt{OSD}$, as well as two-sided p-values for the null hypotheses that the slope coefficients are zero, denoted by NW[p], based on Newey and West (1987) standard errors with optimal bandwidth selected as in Newey and West (1994). Results based on three-month and six-month returns are presented in the left and right panel, respectively. The top and bottom panels contain results for local currency- and US dollar-denominated index returns, respectively. The adjusted R^2, presented as a percentage, is denoted by $\bar{R}^2$. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Three-month return							Six-month return						
	$\beta^{\mathtt{S}}$	NW[p]	$\beta^{\mathtt{GD}}$	NW[p]	$\beta^{\mathtt{OSD}}$	NW[p]	$\bar{R}^2$	$\beta^{\mathtt{S}}$	NW[p]	$\beta^{\mathtt{GD}}$	NW[p]	$\beta^{\mathtt{OSD}}$	NW[p]	$\bar{R}^2$
Local currency														
Canada	−0.08	0.39	0.72	0.05*	0.12	0.27	2.6	0.05	0.76	0.37	0.26	−0.04	0.79	−0.3
France	−0.31	0.01**	0.93	0.07*	0.13	0.41	4.2	−0.33	0.09*	0.82	0.14	−0.04	0.87	1.7
Germany	−0.31	0.04**	1.14	0.02**	0.17	0.25	4.6	−0.36	0.10*	0.89	0.12	0.08	0.72	1.4
Italy	−0.46	0.00***	1.26	0.01**	−0.12	0.60	9.7	−0.53	0.00***	1.14	0.03**	−0.16	0.54	4.9
Japan	−0.20	0.13	0.74	0.03**	−0.01	0.97	2.0	−0.31	0.12	0.46	0.26	−0.21	0.31	1.4
UK	−0.13	0.21	0.49	0.17	0.09	0.46	1.2	−0.01	0.94	0.46	0.25	−0.06	0.70	0.1
US dollar														
Canada	−0.08	0.49	0.97	0.03**	0.19	0.21	3.1	0.11	0.56	0.44	0.34	−0.06	0.76	−0.2
France	−0.19	0.12	1.09	0.03**	0.18	0.27	3.9	−0.23	0.23	0.80	0.13	−0.06	0.78	1.0
Germany	−0.20	0.13	1.31	0.01***	0.21	0.16	5.0	−0.28	0.15	0.88	0.11	0.04	0.84	0.9
Italy	−0.35	0.01***	1.43	0.00***	−0.08	0.73	7.4	−0.48	0.01***	1.14	0.04**	−0.20	0.51	4.0
Japan	−0.09	0.45	0.71	0.01***	−0.09	0.62	1.4	−0.15	0.59	0.60	0.13	−0.44	0.10*	1.8
UK	−0.06	0.57	0.94	0.02**	0.08	0.59	3.9	0.04	0.87	0.70	0.10*	−0.11	0.55	0.8
US	−0.15	0.09*	0.89	0.04**	0.15	0.16	5.1	−0.03	0.85	0.69	0.10*	−0.04	0.78	1.0
World	−0.17	0.08*	1.00	0.01***	0.11	0.38	6.2	−0.12	0.45	0.77	0.05**	−0.14	0.42	1.9

Table 13: **Oil supply, global demand, and oil-specific demand shocks as predictors of long-horizon MSCI index returns: adjusted R-squares over the 1986.01–2015.12 sample period.** This table presents adjusted R^2 for the predictive regression $r_{t,t+h} = \alpha^{\texttt{DEC}} + \beta^{\texttt{S}} x_t^{\texttt{S}} + \beta^{\texttt{GD}} x_t^{\texttt{GD}} + \beta^{\texttt{OSD}} x_t^{\texttt{OSD}} + u_{t+h}^{\texttt{DEC}}$, where $r_{t,t+h}$ is the h-month return on an MSCI index and $x_t^{\texttt{S}}$, $x_t^{\texttt{GD}}$, and $x_t^{\texttt{OSD}}$ are the oil supply, global demand, and oil-specific demand shocks obtained in the oil price change decomposition (8). The adjusted R^2, stated as a percentage, based on one-month to six-month returns are presented. The top and bottom panels contain results, for local currency- and US dollar-denominated index returns, based on the oil price change decompositions resulting from the IS and ES models, respectively.

IS Model OPC Decomposition

	One-month	Two-month	Three-month	Four-month	Five-month	Six-month
Local currency						
Canada	1.6	3.4	3.4	3.5	1.7	0.5
France	2.9	3.9	4.0	4.8	3.4	2.3
Germany	3.0	5.1	4.6	4.2	2.6	1.4
Italy	9.6	11.1	10.9	9.9	6.7	5.2
Japan	1.9	2.7	2.3	2.5	2.1	2.0
UK	2.2	2.6	1.4	3.0	2.0	0.7
US dollar						
Canada	1.5	3.8	3.7	3.5	1.6	0.4
France	1.4	3.1	4.6	4.6	2.9	2.1
Germany	1.9	4.7	5.7	4.4	2.4	1.3
Italy	6.6	8.6	9.0	8.0	5.7	4.9
Japan	0.6	1.8	1.7	2.4	2.3	2.1
UK	2.1	5.3	5.1	5.5	3.6	1.7
US	4.3	5.5	4.9	5.6	3.6	1.9
World	3.7	6.4	6.5	6.9	4.7	3.0

ES Model OPC Decomposition

	One-month	Two-month	Three-month	Four-month	Five-month	Six-month
Local currency						
Canada	1.6	3.1	2.6	2.6	0.9	−0.3
France	3.3	3.9	4.2	5.2	3.9	1.7
Germany	3.1	4.8	4.6	5.6	4.2	1.4
Italy	9.1	10.2	9.7	9.3	7.4	4.9
Japan	3.1	2.7	2.0	2.4	2.2	1.4
UK	3.2	2.7	1.2	2.1	1.5	0.1
US dollar						
Canada	1.5	3.5	3.1	2.7	0.9	−0.2
France	1.1	2.9	3.9	4.6	3.1	1.0
Germany	1.5	4.4	5.0	5.4	3.8	0.9
Italy	5.9	7.8	7.4	7.2	6.0	4.0
Japan	0.7	1.5	1.4	2.2	2.2	1.8
UK	2.3	4.8	3.9	4.2	2.7	0.8
US	4.2	6.0	5.1	4.6	2.9	1.0
World	4.1	6.4	6.2	6.3	4.4	1.9

Table 14: **Correlations between oil supply, global demand, and oil-specific demand shocks and several US macroeconomic variables.** This table presents correlations between the oil supply ($x_t^{\mathtt{S}}$), global demand ($x_t^{\mathtt{GD}}$), and oil-specific demand ($x_t^{\mathtt{OSD}}$) shocks, obtained from the IS and ES models in a real-time fashion, and the log dividend yield (dy), the term spread (tms), the default yield spread (dfy), and the one-month Treasury Bill rate (tbl). Results are presented for the 1986.01–2015.12 sample period. The top and bottom panels show results of the three shocks obtained by oil price change decomposition (8) based on the IS and ES models, respectively.

	IS Model OPC Decomposition			
	dy	tms	dfy	tbl
$x^{\mathtt{S}}$	−0.04	0.01	−0.01	−0.02
$x^{\mathtt{GD}}$	−0.03	0.05	−0.17	0.04
$x^{\mathtt{OSD}}$	−0.08	−0.00	−0.08	0.04
	ES Model OPC Decomposition			
	dy	tms	dfy	tbl
$x^{\mathtt{S}}$	−0.08	0.03	−0.07	0.03
$x^{\mathtt{GD}}$	−0.03	0.04	−0.17	0.04
$x^{\mathtt{OSD}}$	−0.06	−0.03	−0.07	0.03

Table 15: **Robustness checks of the US MSCI index excess return predictive regressions: the role of macroeconomic variables.** This table presents results for the predictive regressions $r^{\mathtt{e}}_{t+1} = \gamma^{\mathtt{P}} + \delta^{\mathtt{P}} g^{\mathtt{P}}_t + \boldsymbol{\theta}'\mathbf{z}_t + v^{\mathtt{P}}_{t+1}$ and $r^{\mathtt{e}}_{t+1} = \gamma^{\mathtt{DEC}} + \beta^{\mathtt{S}} x^{\mathtt{S}}_t + \beta^{\mathtt{GD}} x^{\mathtt{GD}}_t + \beta^{\mathtt{OSD}} x^{\mathtt{OSD}}_t + \boldsymbol{\lambda}'\mathbf{z}_t + v^{\mathtt{DEC}}_{t+1}$ over various sample periods. The variables in these regressions are as follows: (i) $r^{\mathtt{e}}_{t+1}$ is excess return on the US MSCI index, (ii) the oil price change proxy $g^{\mathtt{P}}_t$ is the first principal component obtained from three oil spot price log growth rates, West Texas Intermediate, Dubai, and Arab Light, (iii) $x^{\mathtt{S}}_t$, $x^{\mathtt{GD}}_t$, and $x^{\mathtt{OSD}}_t$ are the oil supply, global demand, and oil-specific demand shocks obtained in the oil price change decomposition (8) based on the IS and ES models, and (iv) $\mathbf{z}_t$ is the vector of macroeconomic variables including the log dividend yield (dy), the term spread (tms), the default yield spread (dfy), and the one-month Treasury Bill rate (tbl). The numbers in square brackets represent two-sided p-values for the null hypotheses that the slope coefficients are zero, based on Newey and West (1987) standard errors with optimal bandwidth selected as in Newey and West (1994). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The adjusted R^2, presented as a percentage, is denoted by $\bar{R}^2$.

				IS Model	ES Model
Sample Period	1983.01–2003.04	1983.01–2015.12	1986.01–2015.12	1986.01–2015.12	1986.01–2015.12
$g^{\mathtt{P}}_t$	-0.11	-0.04	-0.04		
	[0.00***]	[0.28]	[0.25]		
$x^{\mathtt{S}}_t$				-0.34	-0.09
				[0.38]	[0.03**]
$x^{\mathtt{GD}}_t$				0.34	0.38
				[0.00***]	[0.00***]
$x^{\mathtt{OSD}}_t$				-0.06	-0.03
				[0.03**]	[0.55]
dy_t	0.03	0.03	0.03	0.03	0.03
	[0.04**]	[0.00***]	[0.00***]	[0.00***]	[0.00***]
tms_t	-0.78	-0.43	-0.49	-0.57	-0.56
	[0.14]	[0.08*]	[0.08*]	[0.04**]	[0.05**]
dfy_t	-0.32	-1.16	-1.36	-0.99	-0.97
	[0.74]	[0.25]	[0.15]	[0.17]	[0.16]
tbl_t	-0.45	-0.29	-0.33	-0.35	-0.34
	[0.14]	[0.02**]	[0.05**]	[0.03**]	[0.03**]
$\bar{R}^2$	6.3	2.0	2.0	5.7	5.6

Table 16: **Descriptive statistics for predicted excess returns on MSCI indexes: 1986.01–2015.12.** This table presents the annualized mean and standard deviation (STD), and the first three autocorrelations (AC(k), $k = 1, 2, 3$) of MSCI index predicted excess returns using two sets of predictors: (i) four macroeconomic variables, i.e., the log dividend yield, the term spread, the default yield spread, and the one-month Treasury Bill rate and (ii) the oil supply, global demand, and oil-specific demand shocks obtained from the oil price decomposition. The top panel contains the results for the MSCI US index based on the macroeconomic variables. The second and third panels contain the results for MSCI local currency- and US dollar-denominated indexes based on the oil price change decomposition resulting from the IS and ES models, respectively.

	Mean	STD	AC(1)	AC(2)	AC(3)
Macroeconomic Variables					
US	7.76	2.56	0.97	0.93	0.90
IS Model OPC Decomposition					
Local currency					
Canada	4.79	2.32	0.56	0.14	−0.09
France	6.04	3.76	0.32	−0.03	−0.11
Germany	5.74	4.25	0.36	−0.01	−0.12
Italy	2.50	7.36	0.28	−0.03	−0.09
Japan	3.62	3.28	0.39	0.05	−0.09
UK	4.21	2.74	0.27	0.00	−0.09
US dollar					
Canada	6.79	2.94	0.61	0.19	−0.07
France	7.96	3.22	0.38	−0.03	−0.13
Germany	7.15	3.81	0.41	−0.02	−0.13
Italy	5.24	6.90	0.30	−0.04	−0.10
Japan	3.29	2.65	0.31	−0.02	−0.07
UK	6.68	3.02	0.46	0.09	−0.10
US	7.77	3.44	0.44	0.04	−0.12
World	6.35	3.24	0.43	0.06	−0.11
ES Model OPC Decomposition					
Local currency					
Canada	4.79	2.30	0.52	0.16	−0.01
France	6.01	3.97	0.34	0.12	−0.02
Germany	5.72	4.33	0.36	0.11	−0.03
Italy	2.49	7.19	0.29	0.03	−0.06
Japan	3.60	3.94	0.41	0.14	−0.01
UK	4.18	3.13	0.32	0.13	−0.01
US dollar					
Canada	6.78	2.92	0.56	0.20	0.02
France	7.95	2.98	0.37	0.09	−0.04
Germany	7.13	3.50	0.39	0.09	−0.05
Italy	5.24	6.59	0.27	−0.01	−0.08
Japan	3.28	2.65	0.37	0.13	−0.01
UK	6.66	3.14	0.45	0.14	−0.02
US	7.76	3.40	0.43	0.10	−0.05
World	6.33	3.40	0.43	0.12	−0.03

Table 17: **Descriptive statistics for predicted excess returns on MSCI indexes: 1996.01–2012.01.** This table presents the mean, the standard deviation (STD), and the first three autocorrelations (AC(k), $k = 1, 2, 3$) of MSCI index predicted excess returns using two sets of predictors: (i) four macroeconomic variables, i.e., the log dividend yield, the term spread, the default yield spread, and the one-month Treasury Bill rate and (ii) the oil supply, global demand, and oil-specific demand shocks obtained from the oil price decomposition. For comparison purposes, the top panel reports the descriptive statistics for the US equity premium estimates of Martin (2017), obtained from option prices, for one-month (M1), two-month (M2), three-month (M3), six-month (M6), and one-year (M12) maturities. The second panel contains the results for the MSCI US index based on the macroeconomic variables. The third (fourth) panel contains the results for MSCI local currency-denominated (US dollar-denominated) indexes based on the oil price decomposition.

	Mean	STD	AC(1)	AC(2)	AC(3)
Martin (2017)'s US Equity Premium					
M1	4.93	3.99	0.78	0.55	0.45
M2	4.97	3.65	0.82	0.61	0.51
M3	4.93	3.35	0.85	0.67	0.57
M6	4.87	2.85	0.88	0.73	0.64
M12	4.64	2.38	0.90	0.80	0.72
Macroeconomic Variables					
US	4.89	3.42	0.94	0.87	0.81
IS Model OPC Decomposition					
Local currency					
Canada	6.98	4.25	0.65	0.19	−0.09
France	5.18	5.23	0.51	−0.00	−0.17
Germany	5.75	6.78	0.47	−0.06	−0.19
Italy	2.55	6.21	0.42	−0.03	−0.16
Japan	−2.19	3.66	0.65	0.22	−0.04
UK	2.52	3.21	0.38	−0.01	−0.12
US dollar					
Canada	10.19	5.72	0.67	0.23	−0.06
France	5.57	5.20	0.54	0.05	−0.15
Germany	6.09	6.62	0.49	−0.02	−0.18
Italy	4.19	6.21	0.46	0.01	−0.14
Japan	−2.60	3.04	0.54	0.04	−0.03
UK	4.34	4.76	0.62	0.17	−0.08
US	4.73	5.36	0.54	0.06	−0.14
World	3.61	4.84	0.57	0.11	−0.11
ES Model OPC Decomposition					
Local currency					
Canada	6.96	4.38	0.65	0.23	−0.02
France	5.12	5.22	0.51	0.14	−0.04
Germany	5.65	6.27	0.46	0.08	−0.07
Italy	2.52	6.66	0.42	0.10	−0.05
Japan	−2.17	3.73	0.64	0.21	−0.03
UK	2.53	4.40	0.37	0.13	−0.01
US dollar					
Canada	10.15	5.72	0.69	0.28	0.00
France	5.52	5.08	0.55	0.14	−0.06
Germany	6.01	6.18	0.47	0.06	−0.08
Italy	4.17	6.41	0.46	0.10	−0.06
Japan	−2.52	2.15	0.67	0.27	−0.01
UK	4.34	5.38	0.58	0.21	−0.01
US	4.68	5.49	0.55	0.15	−0.05
World	3.59	4.98	0.57	0.17	−0.04

Figure 1: **Scatter plots of US dollar-denominated MSCI World index excess return versus the one-month lagged log growth rate of West Texas Intermediate (WTI) spot price.** In this figure, we present the scatter plots of the US dollar-denominated MSCI World index return versus the one-month lagged log growth rate of WTI spot price over the 1982.01–2003.12 and 2004.01–2015.12 sample periods. The solid lines represent the fitted least-squares regression lines. The correlation between the MSCI World index excess return and the one-month lagged log growth rate of WTI spot price is -0.22, 0.25, and -0.04 over the 1982.01–2003.12, 2004.01–2015.12, and 1982.01–2015.12 sample periods, respectively.

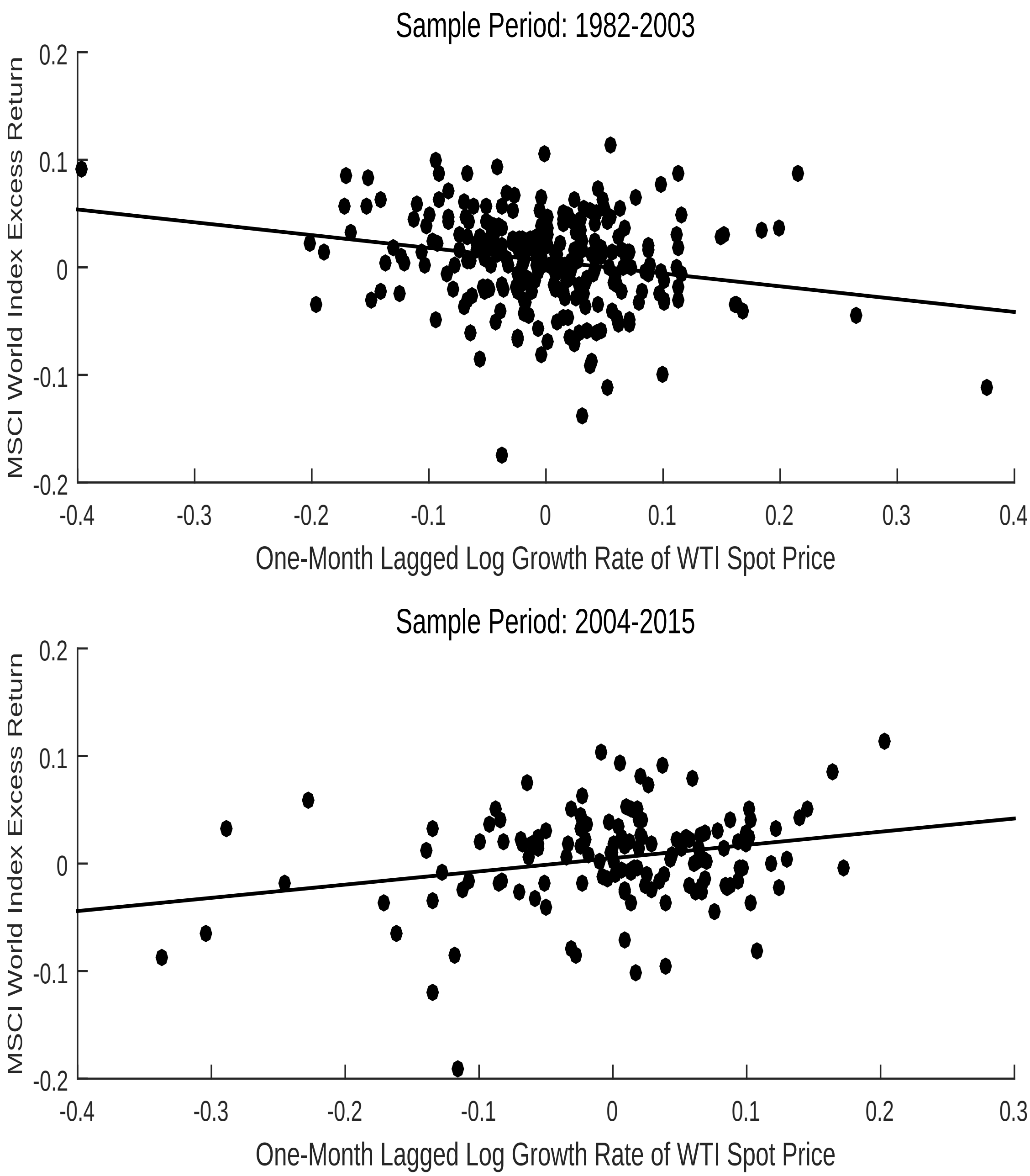


Figure 2: **Time series of oil price change and global demand growth proxies.** In the first figure, we plot the log growth rates of three oil spot price proxies, i.e., WTI, Dubai, and Arab Light, along with their first principal component, $g^{\mathtt{P}}$, over the 1983.01–2015.12 sample period. The series are rescaled so that they have a standard deviation equal to 0.09. In the second figure, we plot the log growth rates of the shipping cost index and the seasonally-adjusted crude steel production, along with their first principal component, $g^{\mathtt{GD}}$, over the 1983.01–2015.12 sample period. The series are rescaled so that they have a standard deviation equal to 0.12.

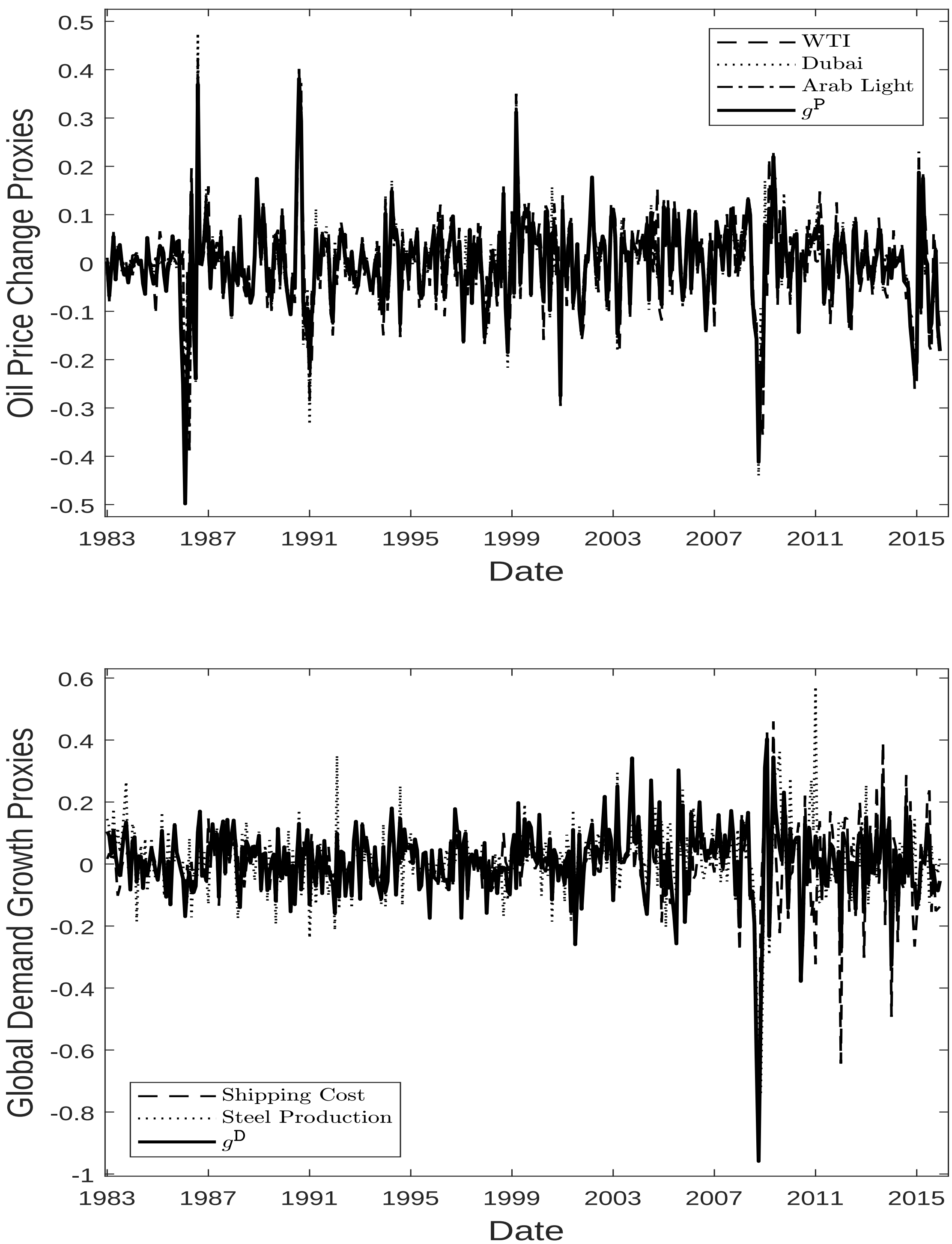


Figure 3: **Oil supply and demand elasticities consistent with the estimates of the reduced-form VAR model.** In this figure, we plot the pairs of supply and demand elasticities $(\eta_{\mathtt{S}}, \eta_{\mathtt{D}})$ that are consistent with the estimates of the reduced-form VAR model (4). The circle corresponds to the independent IV estimates $(\eta^*_{\mathtt{S}}, \eta^*_{\mathtt{D}}) = (0.077, -0.074)$ of Caldara, Cavallo, and Iacoviello (2017). The square corresponds to the pair of optimal admissible elasticities $(\widehat{\eta}_{\mathtt{S}}, \widehat{\eta}_{\mathtt{D}}) = (0.157, -0.136)$.

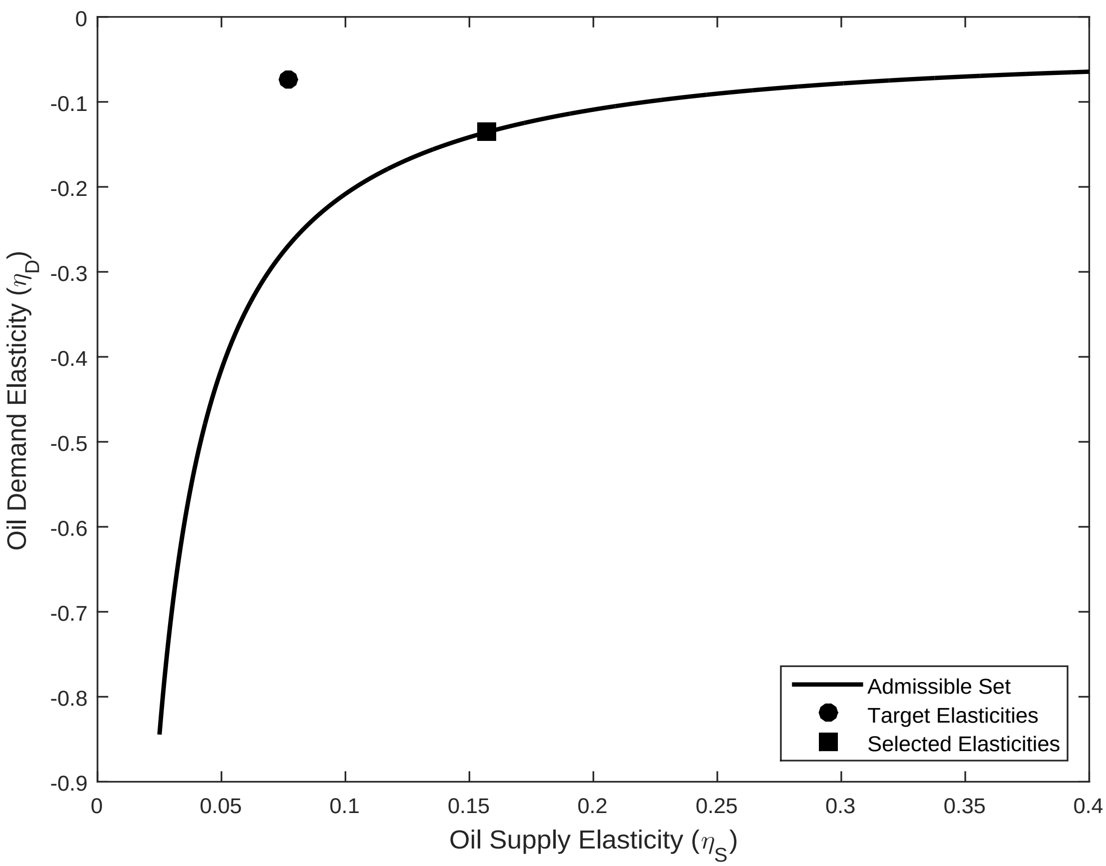


Figure 4: **Variance decomposition of oil price changes according to the ES model.** In this figure, we plot the percentages of the oil price variance attributed to the oil supply and oil-specific demand shocks based on the estimates of the ES model.

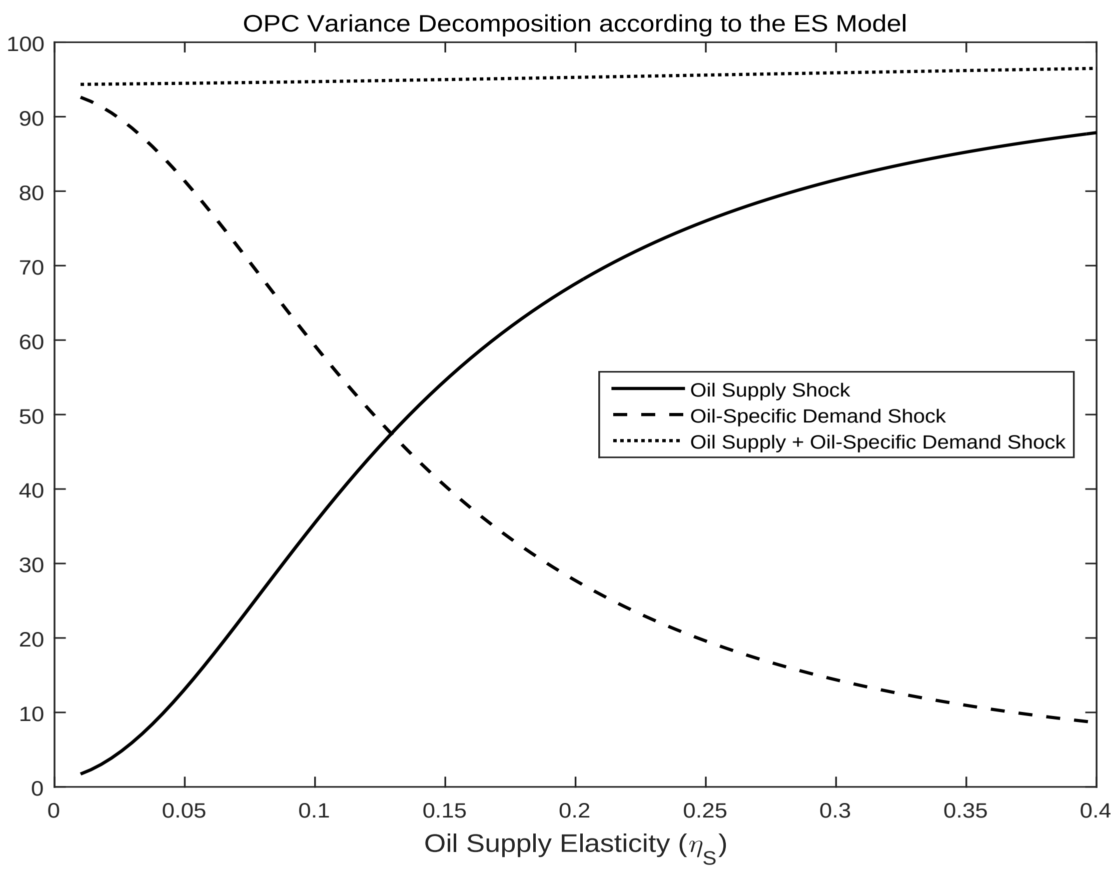
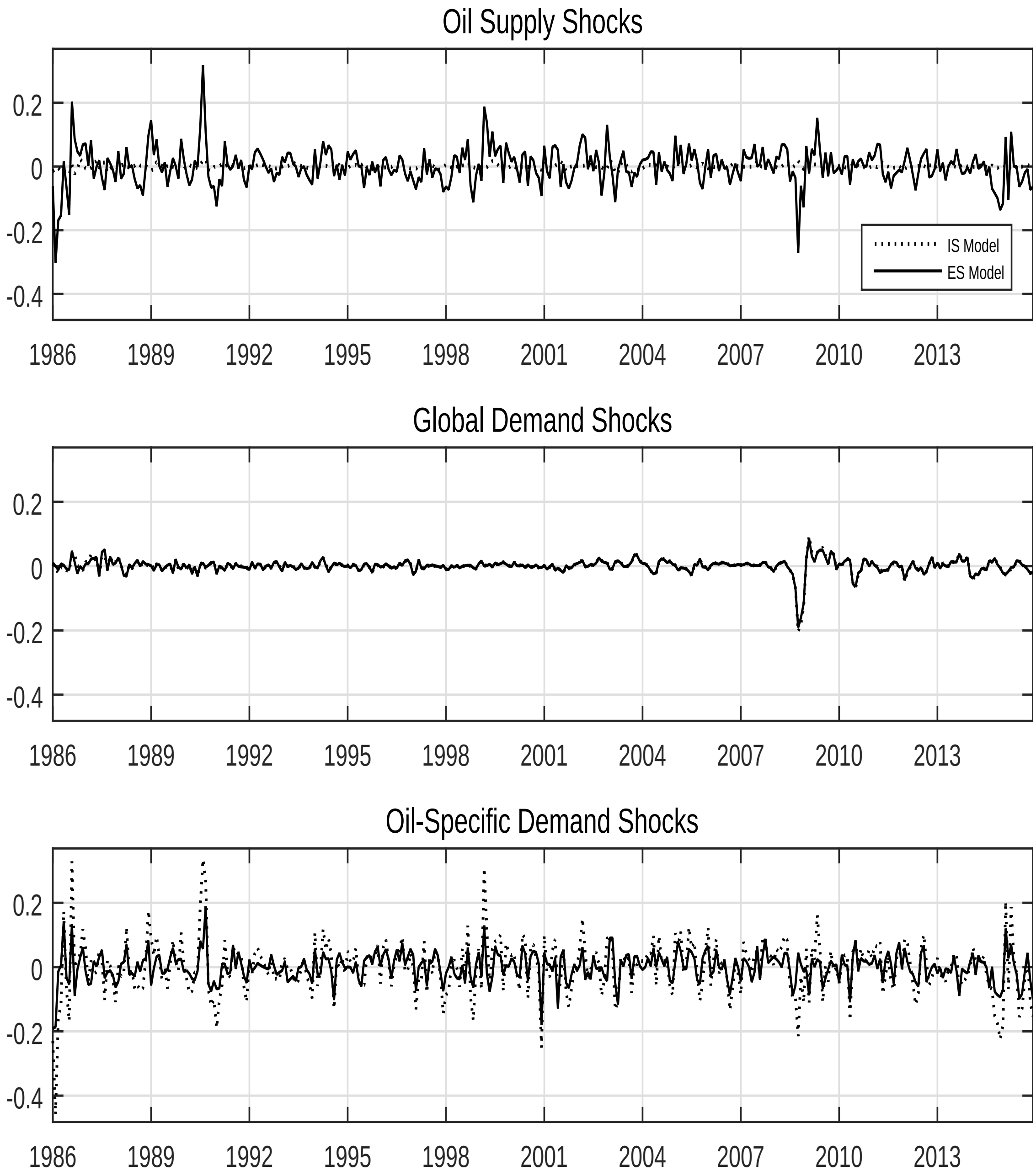


Figure 5: **Time series of oil supply, global demand, and oil-specific demand shocks.** In this figure, we plot the time series of the oil supply, global demand, and oil-specific demand shocks obtained using the decomposition in equation (8), based on the IS and ES models, over the 1986.01–2015.12 sample period. The shocks are obtained in a real-time fashion as described in section 4.



Online Appendix for

"Oil and Equity Return Predictability: The Importance of Dissecting Oil Price Changes"

In this Online Appendix, we provide additional results and robustness checks. In Table A1, we report results on the economic significance of the predictive ability of oil price change in terms of the CER and the SR of the associated optimal trading strategies for a mean-variance investor with a risk aversion coefficient $\gamma = 3$. In Tables A2 and A3, we present predictive regression estimation results for MSCI indexes based on (i) the oil price change and (ii) the oil supply, global demand, and oil-specific demand shocks obtained from the IS and the ES models, respectively, using Hodrick (1992) standard errors. In Table A4, we report Bai and Perron (2003) structural break test results for the regressions using (i) oil price change and (ii) the oil supply, global demand, and oil-specific demand shocks to forecast the Fama-French 17 industry portfolio excess returns. In Tables A5 and A6, we present predictive regression estimation results for the Fama-French 17 industry portfolios based on (i) the oil price change and (ii) the oil supply, global demand, and oil-specific demand shocks obtained from the IS and the ES models, respectively. In Tables A7 and A8, we report estimation results for an augmented EGARCH(1,1) model that includes the oil supply, global demand, and oil-specific demand shocks in the volatility equation as exogenous regressors for the IS and the ES models, respectively. In Figures A1 and A2, we present the slope estimates for the predictive regression model (1) over different samples using an expanding window for local currency- and US dollar-denominated MSCI index returns, respectively.

Table A1: **Oil price change as a predictor of MSCI index excess returns: economic significance over the 1983.01–2003.04 and 1983.01–2015.12 sample periods.** This table presents evidence on the performance of the optimal trading strategies using oil price change as a predictor in terms of two metrics: the certainty equivalent return (CER) and the Sharpe ratio (SR). The investor forms optimal mean-variance portfolios between an MSCI index and the corresponding Treasury Bill and has a risk aversion coefficient $\gamma = 3$. The weight on the MSCI index is constrained between $\underline{\omega} = 0$ and $\overline{\omega} = 150\%$. We compare the baseline model (IID), according to which the MSCI index excess return r^{e}_{t+1} is i.i.d., to the alternative model (P) described by the predictive regression $r^{\mathsf{e}}_{t+1} = \alpha^{\mathsf{P}} + \delta^{\mathsf{P}} g^{\mathsf{P}}_t + u^{\mathsf{P}}_{t+1}$, where the oil price change proxy g^{P}_t is the first principal component obtained from three oil spot price log growth rates: West Texas Intermediate, Dubai, and Arab Light. The portfolio strategies use the mean and variance estimates resulting from each model, respectively. Reported are the CERs in annualized percentage points and the annualized SRs for both baseline and alternative models. We also report the one-sided p-values for the null hypothesis that the alternative model does not improve the CER and SR obtained from the optimal trading strategy based on the baseline model. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The top and bottom panels contain results for local currency- and US dollar-denominated index returns, respectively. The results are based on an expanding window with 60 initial observations.

	1983.01–2003.04						1983.01–2015.12					
	CER			SR			CER			SR		
	P	IID	p-value	P	IID	p-value	P	IID	p-value	P	IID	p-value
Local currency												
Canada	9.65	5.56	0.04**	0.49	0.07	0.02**	5.59	5.10	0.39	0.29	0.23	0.37
France	12.26	6.19	0.05**	0.61	0.28	0.04**	7.08	5.24	0.23	0.44	0.31	0.22
Germany	13.11	4.10	0.01**	0.72	0.22	0.01***	7.21	4.59	0.18	0.48	0.30	0.15
Italy	19.11	6.64	0.00***	0.82	−0.06	0.00***	9.30	4.50	0.06*	0.49	−0.01	0.00***
Japan	−1.22	−6.66	0.06*	0.13	−0.23	0.00***	−2.24	−2.83	0.43	0.06	−0.08	0.19
UK	11.91	5.81	0.00***	0.54	0.08	0.00***	7.93	5.21	0.06*	0.42	0.18	0.04**
US dollar												
Canada	7.28	4.20	0.15	0.38	0.12	0.11	3.25	3.85	0.60	0.23	0.25	0.55
France	10.67	5.47	0.06*	0.59	0.36	0.06*	4.78	4.32	0.43	0.38	0.35	0.41
Germany	11.70	3.80	0.02**	0.64	0.23	0.01**	4.73	4.09	0.42	0.38	0.30	0.30
Italy	13.51	2.53	0.00***	0.72	0.07	0.00***	3.97	1.86	0.29	0.37	0.09	0.04**
Japan	−3.83	−6.30	0.11	−0.10	−0.25	0.14	−2.19	−2.27	0.48	−0.07	−0.13	0.25
UK	8.17	4.12	0.02**	0.45	0.21	0.02**	3.91	3.69	0.46	0.29	0.27	0.40
US	11.61	7.81	0.11	0.66	0.45	0.08*	7.74	7.06	0.37	0.52	0.48	0.36
World	7.79	2.26	0.06*	0.43	0.19	0.06*	4.70	3.54	0.30	0.34	0.29	0.36

Table A2: **Oil supply, global demand, and oil-specific demand shocks, based on the IS model, as predictors of MSCI index excess returns: statistical significance results, based on Hodrick (1992) standard errors, over the 1986.01–2015.12 sample period.** The left panel presents in-sample results for the predictive regression $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{P}} + \delta^{\mathtt{P}} g^{\mathtt{P}}_t + u^{\mathtt{P}}_{t+1}$, where $r^{\mathtt{e}}_{t+1}$ is excess return on an MSCI index and the oil price change proxy $g^{\mathtt{P}}_t$ is the first principal component obtained from three oil spot price log growth rates: West Texas Intermediate, Dubai, and Arab Light. The right panel presents in-sample results for the predictive regression $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{DEC}} + \beta^{\mathtt{S}} x^{\mathtt{S}}_t + \beta^{\mathtt{GD}} x^{\mathtt{GD}}_t + \beta^{\mathtt{OSD}} x^{\mathtt{OSD}}_t + u^{\mathtt{DEC}}_{t+1}$, where $x^{\mathtt{S}}_t$, $x^{\mathtt{GD}}_t$, and $x^{\mathtt{OSD}}_t$ are the oil supply, global demand, and oil-specific demand shocks obtained in the oil price change decomposition (8). Shown are the estimates of the predictive slope coefficients $\delta^{\mathtt{P}}$ (left panel) and β^i, $i = \mathtt{S}, \mathtt{GD}, \mathtt{OSD}$ (right panel), as well as two-sided p-values for the null hypotheses that the slope coefficients are zero, denoted by H[p], based on Hodrick (1992) standard errors. The top and bottom panels contain results for local currency- and US dollar-denominated index returns, respectively. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The adjusted R^2, presented as a percentage, is denoted by $\bar{R}^2$.

	Oil Price Change			IS Model OPC Decomposition						
	$\delta^{\mathtt{P}}$	H[p]	$\bar{R}^2$	$\beta^{\mathtt{S}}$	H[p]	$\beta^{\mathtt{GD}}$	H[p]	$\beta^{\mathtt{OSD}}$	H[p]	$\bar{R}^2$
Local currency										
Canada	−0.00	0.87	−0.3	−0.18	0.64	0.27	0.02**	−0.03	0.38	1.5
France	−0.08	0.07*	1.5	−0.43	0.40	0.23	0.10*	−0.10	0.03**	2.9
Germany	−0.08	0.11	1.0	−0.50	0.41	0.31	0.07*	−0.11	0.02**	3.1
Italy	−0.18	0.00***	6.2	−0.75	0.15	0.32	0.03**	−0.22	0.00***	9.5
Japan	−0.05	0.36	0.3	0.21	0.67	0.31	0.03**	−0.08	0.13	1.9
UK	−0.06	0.04**	1.4	0.17	0.70	0.16	0.14	−0.09	0.01***	2.3
US dollar										
Canada	0.02	0.67	−0.2	−0.26	0.56	0.35	0.03**	−0.01	0.82	1.5
France	−0.06	0.22	0.4	−0.57	0.30	0.23	0.26	−0.07	0.11	1.5
Germany	−0.06	0.26	0.3	−0.66	0.30	0.30	0.23	−0.08	0.09*	1.9
Italy	−0.16	0.01***	4.1	−0.91	0.11	0.32	0.11	−0.20	0.00***	6.6
Japan	−0.04	0.44	0.1	0.61	0.28	0.19	0.17	−0.07	0.21	0.7
UK	−0.03	0.40	0.0	0.01	0.98	0.32	0.03**	−0.06	0.10*	2.1
US	−0.04	0.17	0.5	−0.36	0.39	0.32	0.03**	−0.07	0.03**	4.3
World	−0.04	0.23	0.5	−0.19	0.63	0.31	0.03**	−0.07	0.04**	3.6

Table A3: **Oil supply, global demand, and oil-specific demand shocks, based on the ES model, as predictors of MSCI index excess returns: statistical significance results, based on Hodrick (1992) standard errors, over the 1986.01–2015.12 sample period.** The left panel presents in-sample results for the predictive regression $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{P}} + \delta^{\mathtt{P}} g^{\mathtt{P}}_t + u^{\mathtt{P}}_{t+1}$, where $r^{\mathtt{e}}_{t+1}$ is excess return on an MSCI index and the oil price change proxy $g^{\mathtt{P}}_t$ is the first principal component obtained from three oil spot price log growth rates: West Texas Intermediate, Dubai, and Arab Light. The right panel presents in-sample results for the predictive regression $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{DEC}} + \beta^{\mathtt{S}} x^{\mathtt{S}}_t + \beta^{\mathtt{GD}} x^{\mathtt{GD}}_t + \beta^{\mathtt{OSD}} x^{\mathtt{OSD}}_t + u^{\mathtt{DEC}}_{t+1}$, where $x^{\mathtt{S}}_t$, $x^{\mathtt{GD}}_t$, and $x^{\mathtt{OSD}}_t$ are the oil supply, global demand, and oil-specific demand shocks obtained in the oil price change decomposition (8). Shown are the estimates of the predictive slope coefficients $\delta^{\mathtt{P}}$ (left panel) and β^i, $i = \mathtt{S}, \mathtt{GD}, \mathtt{OSD}$ (right panel), as well as two-sided p-values for the null hypotheses that the slope coefficients are zero, denoted by H[p], based on Hodrick (1992) standard errors. The top and bottom panels contain results for local currency- and US dollar-denominated index returns, respectively. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The adjusted R^2, presented as a percentage, is denoted by $\bar{R}^2$.

	Oil Price Change			ES Model OPC Decomposition						
	$\delta^{\mathtt{P}}$	H[p]	$\bar{R}^2$	$\beta^{\mathtt{S}}$	H[p]	$\beta^{\mathtt{GD}}$	H[p]	$\beta^{\mathtt{OSD}}$	H[p]	$\bar{R}^2$
Local currency										
Canada	−0.00	0.87	−0.3	−0.05	0.30	0.30	0.02**	−0.00	0.98	1.5
France	−0.08	0.07*	1.5	−0.18	0.01**	0.31	0.04**	−0.00	1.00	3.3
Germany	−0.08	0.11	1.0	−0.18	0.04**	0.40	0.03**	−0.01	0.88	3.2
Italy	−0.18	0.00***	6.2	−0.25	0.00***	0.39	0.02**	−0.18	0.08*	9.0
Japan	−0.05	0.36	0.3	−0.16	0.06*	0.43	0.01***	0.04	0.62	3.1
UK	−0.06	0.04**	1.4	−0.15	0.00***	0.23	0.06*	0.02	0.71	3.2
US dollar										
Canada	0.02	0.67	−0.2	−0.04	0.45	0.40	0.03**	0.03	0.71	1.5
France	−0.06	0.22	0.4	−0.11	0.13	0.28	0.21	−0.03	0.76	1.1
Germany	−0.06	0.26	0.3	−0.12	0.19	0.35	0.18	−0.04	0.66	1.5
Italy	−0.16	0.01***	4.1	−0.19	0.03**	0.36	0.11	−0.21	0.08*	6.0
Japan	−0.04	0.44	0.1	−0.12	0.18	0.26	0.10*	0.02	0.82	0.7
UK	−0.03	0.40	0.0	−0.11	0.07*	0.37	0.03**	0.01	0.85	2.3
US	−0.04	0.17	0.5	−0.10	0.03**	0.38	0.02**	−0.03	0.56	4.2
World	−0.04	0.23	0.5	−0.12	0.04**	0.38	0.02**	−0.01	0.89	4.1

Table A4: **Bai-Perron structural break tests for excess returns on Fama-French 17 value-weighted industry portfolios: oil price change as the predictor over the 1983.01–2015.12 sample period, and oil supply, global demand,and oil-specific demand shocks, based on the IS and the ES models, as predictors over the 1986.01–2015.12 sample period.** The first column presents Bai and Perron (2003) structural break test results for the predictive regression $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{P}} + \delta^{\mathtt{P}} g^{\mathtt{P}}_t + u^{\mathtt{P}}_{t+1}$, where $r^{\mathtt{e}}_{t+1}$ is excess return on an industry portfolio and the oil price change proxy $g^{\mathtt{P}}_t$ is the first principal component obtained from three oil spot price log growth rates: West Texas Intermediate, Dubai, and Arab Light. The second and third columns present Bai and Perron (2003) structural break test results for the predictive regression $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{DEC}} + \beta^{\mathtt{S}} x^{\mathtt{S}}_t + \beta^{\mathtt{GD}} x^{\mathtt{GD}}_t + \beta^{\mathtt{OSD}} x^{\mathtt{OSD}}_t + u^{\mathtt{DEC}}_{t+1}$, where $r^{\mathtt{e}}_{t+1}$ is excess return on an industry portfolio and $x^{\mathtt{S}}_t$, $x^{\mathtt{GD}}_t$, $x^{\mathtt{OSD}}_t$ are the oil supply, global demand, oil-specific demand shocks obtained in the oil price change decomposition (8), based on the IS and ES models, respectively. The number of breaks is selected by the Bayesian Information Criterion (BIC).

	Oil Price Change		IS Model OPC Decomposition	ES Model OPC Decomposition
	# of breaks selected by BIC	Break date	# of breaks selected by BIC	# of breaks selected by BIC
Food	1	1991.12	0	0
Mines	0	–	0	0
Oil	0	–	0	0
Clths	1	2008.08	0	0
Durbl	1	2008.06	0	0
Chems	1	2008.07	0	0
Cnsum	1	2000.05	0	0
Cnstr	1	2008.08	0	0
Steel	1	2008.07	0	0
FabPr	1	2008.08	0	0
Machn	1	2008.08	0	0
Cars	1	2008.08	0	0
Trans	1	2008.06	0	0
Utils	0	–	0	0
Rtail	1	2008.08	0	0
Finan	1	2008.06	0	0
Other	1	2008.08	0	0

Table A5: **Oil supply, global demand, and oil-specific demand shocks, based on the IS model, as predictors of excess returns on Fama-French 17 value-weighted industry portfolios: statistical significance over the 1986.01–2015.12 sample period.** The left panel presents in-sample results for the predictive regression $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{P}} + \delta^{\mathtt{P}} g^{\mathtt{P}}_t + u^{\mathtt{P}}_{t+1}$, where $r^{\mathtt{e}}_{t+1}$ is excess return on an industry portfolio and the oil price change proxy $g^{\mathtt{P}}_t$ is the first principal component obtained from three oil spot price log growth rates: West Texas Intermediate, Dubai, and Arab Light. The right panel presents in-sample results for the predictive regression $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{DEC}} + \beta^{\mathtt{S}} x^{\mathtt{S}}_t + \beta^{\mathtt{GD}} x^{\mathtt{GD}}_t + \beta^{\mathtt{OSD}} x^{\mathtt{OSD}}_t + u^{\mathtt{DEC}}_{t+1}$, where $r^{\mathtt{e}}_{t+1}$ is excess return on an industry portfolio and $x^{\mathtt{S}}_t$, $x^{\mathtt{GD}}_t$, and $x^{\mathtt{OSD}}_t$ are the oil supply, global demand, and oil-specific demand shocks obtained in the oil price change decomposition (8), based on the IS model. Shown are the estimates of the predictive slope coefficients $\delta^{\mathtt{P}}$ (left panel) and β^i, $i = \mathtt{S}, \mathtt{GD}, \mathtt{OSD}$ (right panel), as well as two-sided p-values for the null hypotheses that the slope coefficients are zero, denoted by NW[p], based on Newey and West (1987) standard errors with optimal bandwidth selected as in Newey and West (1994). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The adjusted R^2, presented as a percentage, is denoted by $\bar{R}^2$.

	Oil Price Change			IS Model OPC Decomposition						
	$\delta^{\mathtt{P}}$	NW[p]	$\bar{R}^2$	$\beta^{\mathtt{S}}$	NW[p]	$\beta^{\mathtt{GD}}$	NW[p]	$\beta^{\mathtt{OSD}}$	NW[p]	$\bar{R}^2$
Food	−0.028	0.45	0.1	−0.36	0.39	0.15	0.11	−0.04	0.23	0.9
Mines	0.018	0.74	−0.2	−0.69	0.28	0.34	0.06*	0.01	0.92	0.6
Oil	0.004	0.90	−0.3	−0.04	0.93	0.12	0.30	−0.00	0.91	−0.6
Clths	−0.077	0.22	1.0	−1.13	0.05*	0.52	0.00***	−0.12	0.01**	7.5
Durbl	−0.025	0.66	−0.1	−0.39	0.44	0.53	0.00***	−0.07	0.11	4.9
Chems	0.018	0.76	−0.2	−0.59	0.22	0.56	0.00***	−0.02	0.72	4.7
Cnsum	−0.042	0.29	0.5	−0.37	0.37	0.13	0.15	−0.05	0.16	1.0
Cnstr	−0.085	0.09*	1.5	−0.78	0.15	0.34	0.02**	−0.11	0.00***	4.7
Steel	−0.001	0.98	−0.3	−0.56	0.38	0.59	0.01**	−0.04	0.51	2.5
FabPr	−0.020	0.65	−0.2	−0.39	0.41	0.30	0.01***	−0.04	0.34	1.5
Machn	−0.064	0.32	0.4	−0.24	0.70	0.53	0.00***	−0.12	0.02**	3.9
Cars	−0.058	0.32	0.4	−0.85	0.09*	0.43	0.01**	−0.09	0.04**	3.6
Trans	−0.028	0.50	−0.0	−0.31	0.52	0.43	0.00***	−0.07	0.08*	4.1
Utils	0.005	0.87	−0.3	−0.55	0.08*	0.07	0.33	0.01	0.76	0.4
Rtail	−0.094	0.01***	2.6	−0.40	0.40	0.26	0.03**	−0.12	0.00***	5.1
Finan	−0.041	0.51	0.2	−0.80	0.09*	0.54	0.00***	−0.08	0.04**	7.0
Other	−0.055	0.22	0.7	−0.24	0.59	0.37	0.01***	−0.09	0.01***	4.2

Table A6: **Oil supply, global demand, and oil-specific demand shocks, based on the ES model, as predictors of excess returns on Fama-French 17 value-weighted industry portfolios: statistical significance over the 1986.01–2015.12 sample period.** The left panel presents in-sample results for the predictive regression $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{P}} + \delta^{\mathtt{P}} g^{\mathtt{P}}_t + u^{\mathtt{P}}_{t+1}$, where $r^{\mathtt{e}}_{t+1}$ is excess return on an industry portfolio and the oil price change proxy $g^{\mathtt{P}}_t$ is the first principal component obtained from three oil spot price log growth rates: West Texas Intermediate, Dubai, and Arab Light. The right panel presents in-sample results for the predictive regression $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{DEC}} + \beta^{\mathtt{S}} x^{\mathtt{S}}_t + \beta^{\mathtt{GD}} x^{\mathtt{GD}}_t + \beta^{\mathtt{OSD}} x^{\mathtt{OSD}}_t + u^{\mathtt{DEC}}_{t+1}$, where $r^{\mathtt{e}}_{t+1}$ is excess return on an industry portfolio and $x^{\mathtt{S}}_t$, $x^{\mathtt{GD}}_t$, and $x^{\mathtt{OSD}}_t$ are the oil supply, global demand, and oil-specific demand shocks obtained in the oil price change decomposition (8), based on the ES model. Shown are the estimates of the predictive slope coefficients $\delta^{\mathtt{P}}$ (left panel) and β^i, $i = \mathtt{S}, \mathtt{GD}, \mathtt{OSD}$ (right panel), as well as two-sided p-values for the null hypotheses that the slope coefficients are zero, denoted by NW[p], based on Newey and West (1987) standard errors with optimal bandwidth selected as in Newey and West (1994). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The adjusted R^2, presented as a percentage, is denoted by $\bar{R}^2$.

	Oil Price Change			ES Model OPC Decomposition						
	$\delta^{\mathtt{P}}$	NW[p]	$\bar{R}^2$	$\beta^{\mathtt{S}}$	NW[p]	$\beta^{\mathtt{GD}}$	NW[p]	$\beta^{\mathtt{OSD}}$	NW[p]	$\bar{R}^2$
Food	−0.028	0.45	0.1	−0.11	0.00***	0.22	0.08*	0.04	0.41	1.5
Mines	0.018	0.74	−0.2	−0.03	0.75	0.39	0.13	0.02	0.90	0.2
Oil	0.004	0.90	−0.3	−0.06	0.25	0.18	0.24	0.07	0.30	−0.2
Clths	−0.077	0.22	1.0	−0.14	0.03**	0.58	0.00***	−0.11	0.13	5.9
Durbl	−0.025	0.66	−0.1	−0.07	0.21	0.54	0.01***	−0.06	0.45	4.1
Chems	0.018	0.76	−0.2	−0.07	0.31	0.63	0.00***	0.03	0.76	4.2
Cnsum	−0.042	0.29	0.5	−0.13	0.00***	0.22	0.08*	0.04	0.52	1.8
Cnstr	−0.085	0.09*	1.5	−0.15	0.01***	0.41	0.02**	−0.08	0.31	4.1
Steel	−0.001	0.98	−0.3	−0.05	0.54	0.64	0.01***	−0.05	0.68	2.3
FabPr	−0.020	0.65	−0.2	−0.09	0.17	0.37	0.01***	0.01	0.94	1.5
Machn	−0.064	0.32	0.4	−0.10	0.14	0.56	0.00***	−0.14	0.16	4.0
Cars	−0.058	0.32	0.4	−0.07	0.29	0.43	0.03**	−0.13	0.18	2.6
Trans	−0.028	0.50	−0.0	−0.08	0.13	0.47	0.00***	−0.05	0.41	4.0
Utils	0.005	0.87	−0.3	−0.07	0.10*	0.16	0.18	0.09	0.12	0.8
Rtail	−0.094	0.01***	2.6	−0.15	0.00***	0.31	0.03**	−0.09	0.16	4.9
Finan	−0.041	0.51	0.2	−0.14	0.01**	0.64	0.00***	−0.02	0.74	6.4
Other	−0.055	0.22	0.7	−0.11	0.01***	0.43	0.00***	−0.06	0.41	4.3

Table A7: **Effect of oil supply, global demand, and oil-specific demand shocks, based on the IS model, on conditional return volatility: evidence from an EGARCH(1,1) model.** This table presents results of an augmented EGARCH(1,1) model that includes the three shocks in the volatility equation as exogenous regressors. The econometric specification is: $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{DEC}} + \beta^{\mathtt{S}} x^{\mathtt{S}}_t + \beta^{\mathtt{GD}} x^{\mathtt{GD}}_t + \beta^{\mathtt{OSD}} x^{\mathtt{OSD}}_t + u^{\mathtt{DEC}}_{t+1}$, with $u^{\mathtt{DEC}}_{t+1} = \sigma_t z_{t+1}$, $z_{t+1} \sim$ i.i.d.$(0,1)$, and $\log(\sigma^2_t) = \tau_0 + \tau_1|z_t| + \tau_2 z_t + \tau_3 \log(\sigma^2_{t-1}) + \zeta^{\mathtt{S}} x^{\mathtt{S}}_t + \zeta^{\mathtt{GD}} x^{\mathtt{GD}}_t + \zeta^{\mathtt{OSD}} x^{\mathtt{OSD}}_t$. The reported results are based on the Student-t distribution for the disturbances z_{t+1}. The model is estimated using monthly excess returns on the MSCI indexes for the G7 countries as well as the World MSCI index over the 1986.01–2015.12 sample period. The top and bottom panels contain results for local currency- and US dollar-denominated index returns, respectively. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	τ_1	p-value	τ_2	p-value	τ_3	p-value	$\zeta^{\mathtt{S}}$	p-value	$\zeta^{\mathtt{GD}}$	p-value	$\zeta^{\mathtt{OSD}}$	p-value
Local currency												
Canada	0.16	0.03**	0.07	0.11	0.97	0.00***	−2.98	0.59	−3.16	0.04**	−0.03	0.96
France	0.33	0.00***	−0.20	0.00***	0.81	0.00***	3.05	0.75	0.07	0.98	−0.04	0.95
Germany	0.28	0.01**	−0.09	0.15	0.87	0.00***	6.73	0.45	−2.21	0.36	0.18	0.81
Italy	0.13	0.11	−0.07	0.04**	0.96	0.00***	7.24	0.24	−2.46	0.15	−0.02	0.97
Japan	−0.00	0.97	−0.04	0.43	−0.79	0.00***	6.13	0.70	−8.56	0.05*	−0.02	0.98
UK	0.28	0.03**	−0.17	0.05**	0.78	0.00***	0.19	0.98	1.02	0.69	0.14	0.86
US dollar												
Canada	0.13	0.04**	0.08	0.09*	0.96	0.00***	−4.59	0.38	−3.49	0.02**	−0.40	0.49
France	0.14	0.11	−0.21	0.00***	0.89	0.00***	5.37	0.45	−0.60	0.71	−0.27	0.58
Germany	0.21	0.04**	−0.08	0.17	0.92	0.00***	5.43	0.46	−1.85	0.32	−0.20	0.73
Italy	−0.07	0.03**	−0.02	0.54	0.98	0.00***	11.79	0.00***	−4.52	0.00***	0.26	0.52
Japan	0.00	0.95	−0.07	0.00***	0.99	0.00***	−4.64	0.30	−2.43	0.04**	0.29	0.33
UK	0.14	0.12	−0.11	0.06*	0.94	0.00***	−1.03	0.88	−0.20	0.91	−0.23	0.70
US	0.25	0.03**	−0.18	0.03**	0.86	0.00***	−3.60	0.66	−0.37	0.86	−0.29	0.66
World	0.16	0.12	−0.18	0.02**	0.85	0.00***	4.40	0.61	−0.63	0.75	−0.22	0.73

Table A8: **Effect of oil supply, global demand, and oil-specific demand shocks, based on the ES model, on conditional return volatility: evidence from an EGARCH(1,1) model.** This table presents results of an augmented EGARCH(1,1) model that includes the three shocks in the volatility equation as exogenous regressors. The econometric specification is: $r^{\mathtt{e}}_{t+1} = \alpha^{\mathtt{DEC}} + \beta^{\mathtt{S}} x^{\mathtt{S}}_t + \beta^{\mathtt{GD}} x^{\mathtt{GD}}_t + \beta^{\mathtt{OSD}} x^{\mathtt{OSD}}_t + u^{\mathtt{DEC}}_{t+1}$, with $u^{\mathtt{DEC}}_{t+1} = \sigma_t z_{t+1}$, $z_{t+1} \sim$ i.i.d.$(0,1)$, and $\log(\sigma^2_t) = \tau_0 + \tau_1 |z_t| + \tau_2 z_t + \tau_3 \log(\sigma^2_{t-1}) + \zeta^{\mathtt{S}} x^{\mathtt{S}}_t + \zeta^{\mathtt{GD}} x^{\mathtt{GD}}_t + \zeta^{\mathtt{OSD}} x^{\mathtt{OSD}}_t$. The reported results are based on the Student-t distribution for the disturbances z_{t+1}. The model is estimated using monthly excess returns on the MSCI indexes for the G7 countries as well as the World MSCI index over the 1986.01–2015.12 sample period. The top and bottom panels contain results for local currency- and US dollar-denominated index returns, respectively. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	τ_1	p-value	τ_2	p-value	τ_3	p-value	$\zeta^{\mathtt{S}}$	p-value	$\zeta^{\mathtt{GD}}$	p-value	$\zeta^{\mathtt{OSD}}$	p-value
Local currency												
Canada	0.18	0.02**	0.06	0.27	0.95	0.00***	−0.04	0.96	−2.80	0.11	0.05	0.97
France	0.33	0.00***	−0.20	0.00***	0.80	0.00***	0.20	0.79	0.04	0.99	−0.23	0.86
Germany	0.31	0.01***	−0.10	0.14	0.86	0.00***	0.43	0.61	−2.48	0.32	0.09	0.95
Italy	0.15	0.07*	−0.08	0.01***	0.96	0.00***	0.19	0.71	−2.79	0.13	0.20	0.84
Japan	0.02	0.76	−0.06	0.03**	0.93	0.00***	0.81	0.19	−2.68	0.04**	−0.71	0.45
UK	0.27	0.03**	−0.20	0.01**	0.73	0.00***	1.77	0.13	−0.26	0.93	−3.12	0.09*
US dollar												
Canada	0.14	0.03**	0.07	0.18	0.96	0.00***	−0.37	0.65	−3.22	0.06*	−0.44	0.75
France	0.14	0.11	−0.20	0.00***	0.89	0.00***	0.37	0.46	−1.15	0.45	−1.02	0.36
Germany	0.23	0.03**	−0.08	0.15	0.91	0.00***	−0.00	1.00	−1.86	0.34	−0.47	0.72
Italy	0.08	0.16	−0.10	0.01**	0.95	0.00***	0.24	0.64	−3.57	0.04**	−0.18	0.85
Japan	0.01	0.83	−0.06	0.01***	1.00	0.00***	−0.13	0.81	−2.02	0.09*	0.50	0.44
UK	0.14	0.11	−0.11	0.06*	0.95	0.00***	−0.16	0.83	−0.01	1.00	−0.28	0.82
US	0.30	0.02**	−0.26	0.00***	0.77	0.00***	1.06	0.29	−1.39	0.54	−2.96	0.08*
World	0.17	0.12	−0.21	0.01***	0.78	0.00***	1.30	0.23	−1.69	0.40	−2.87	0.10*

Figure A1: **Oil price change as a predictor of local currency-denominated MSCI index excess returns: slope estimates over expanding sample periods.** In this figure, we plot the time series of the slope estimates, along with the corresponding 95% confidence intervals based on Newey and West (1987) standard errors, from the predictive regression model (1) over different samples using an expanding window with the first sample being 1983.01–1993.01 and the last sample being 1983.01–2015.12.

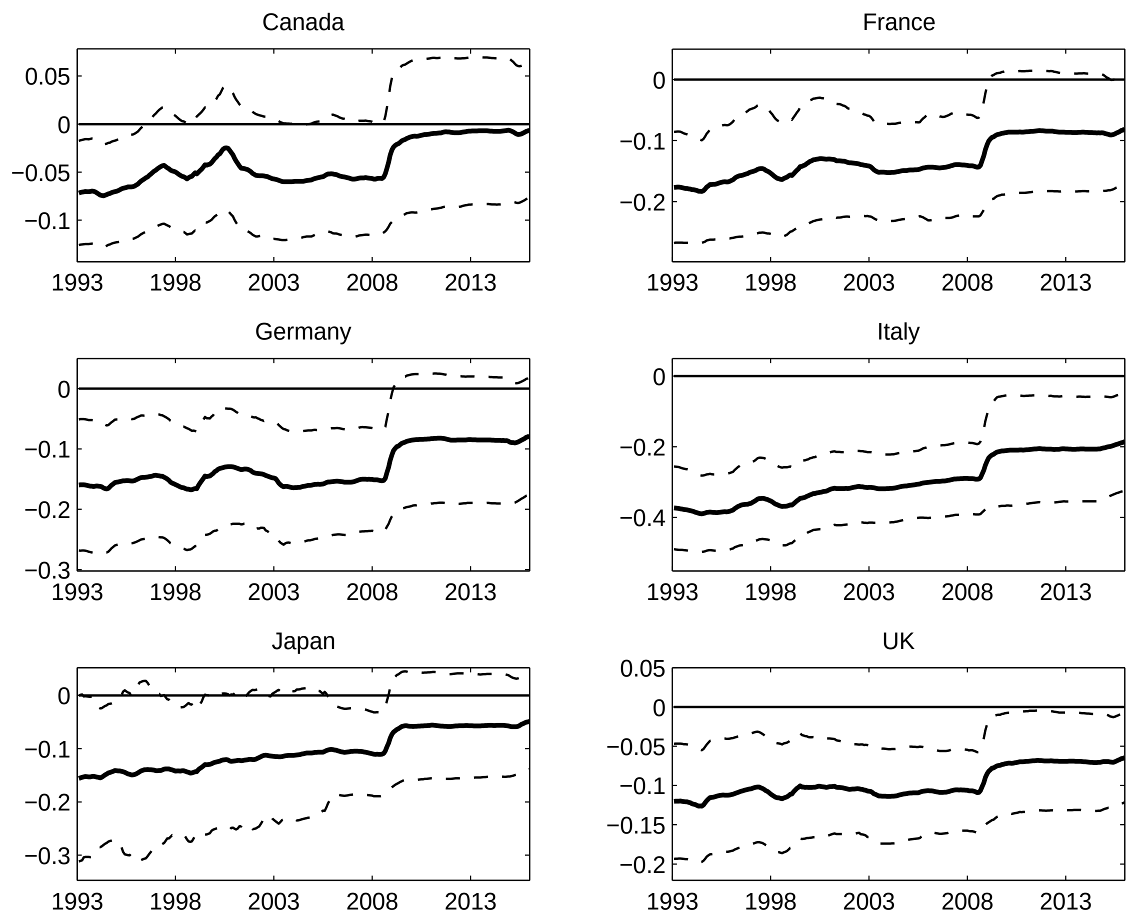


Figure A2: **Oil price change as a predictor of US dollar-denominated MSCI index excess returns: slope estimates over expanding sample periods.** In this figure, we plot the time series of the slope estimates, along with the corresponding 95% confidence intervals based on Newey and West (1987) standard errors, from the predictive regression model (1) over different samples using an expanding window with the first sample being 1983.01–1993.01 and the last sample being 1983.01–2015.12.