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Do oil price shocks drive systematic risk premia in stock markets? A novel investment application☆

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ABSTRACT

This paper examines the effect of oil price shocks on factor returns in a set of 62 stock markets. Oil price shocks capture significant predictive information regarding the size and direction of factor returns in global markets, depending on the market classification and nature of oil shock. Oil supply and precautionary demand shocks possess the greatest predictive power over risk premia, particularly for value and momentum. We argue that time varying investor sentiment and the flexibility of firms to respond to economic shocks drive the responses of factors to oil shocks. More importantly, a conditional global factor investing strategy wherein the investment positions are tilted towards factor-based portfolios, conditional on the size and direction of the oil price shock, yields significant improvements in returns. Our findings show that smart beta strategies can be significantly improved by conditioning factor positions based on the size and direction of oil market shocks.

1. Introduction

Factor investing strategies have raised increasing attention in the investment management sector, resulting in a substantial surge in assets under management for factor ETFs in the U.S., soaring from $20 billion in 2009 to $800 billion by the close of the first quarter of 2023.[1] These strategies identify common characteristics of companies such as value, size and momentum which deliver identifiable and repetitive patterns of return and exploit these predictability patterns to improve portfolio returns and enhance diversification (Balcilar et al., 2021). The trends and cycles for these factors, however, display a great deal of time variation (e.g. Ilmanen et al., 2021; Bessembinder et al., 2023) and often vary with the business cycle as well as investors' perception of risk, thus making it critical for fund managers to design a well-balanced portfolio of multiple factors and tilt factor allocations at different points in the business cycle. Accordingly, this necessitates a better understanding of the predictability of factor premia with respect to economic conditions and uncertainty although the drivers of the time variation in factor returns are largely neglected in the asset pricing literature. Interestingly, the literature on the oil-stock market nexus provides overwhelming evidence that links oil market shocks to the economic

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[1] https://www.blackrock.com/us/individual/investment-ideas/what-is-factor-investing/factor-commentary/andrews-angle/international-style (May 12, 2023)

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variables that are shown to impact asset pricing factors although the literature has not yet established a direct link between oil market shocks and the time variation in factor returns. Against this background, this paper takes an investment perspective to the oil-stock market nexus by exploring the predictability of factor premia from a large set of 62 global stock markets with respect to disaggregated oil market shocks associated with supply, demand and economic activity related factors.

The link between oil market shocks and excess returns on stock market factors is a natural one to argue given the evidence from the investment-based theories in the asset pricing literature that links asset pricing factors to economic shocks that have already been associated with oil price fluctuations in the oil-stock market literature. These theories argue that asset pricing factors respond to economic shocks that impact corporate investment behavior driven by the business cycle, interest rates, growth, and uncertainty.[2] For example, Berk et al. (1999) and Johnson (2002) establish a link between the growth options of firms and the momentum factor, while Lettau and Wachter (2007) and Gormsen and Lazarus (2023) link the value factor to discount rate shocks. Likewise, Hou et al. (2015) link the quality and momentum factors to corporate investment, while, in a separate strand of the literature that deals with rare disasters, Tsai and Wachter (2015) and Gabaix (2012) relate factor returns to tail events. In recent works, however, Bessembinder et al. (2023) show that the composition of economically pertinent factors influencing the cross-section of stock returns fluctuates over time in accordance with economic conditions and the intricacy of firms, while Ilmanen et al. (2021) document some variation in the risk and correlation structure of the factors to the economic environment. Separately, the oil-stock market literature presents overwhelming evidence that establishes a link between oil market shocks and many of the drivers of asset pricing factors including the business cycle (Hamilton, 2011), stock market returns (Kilian and Partk, 2009), personal discretionary spending (Edelstein and Kilian, 2009), corporate investment behavior (Maghyereh and Abdoh, 2020), equity financing costs (Prodromou and Demirer, 2022) and economic uncertainty (Sheng et al., 2020), although the literature has not directly linked these economic shocks to the time variation in factor returns.

From a risk-based perspective, following the arguments by Elder and Serletis (2010), Kang et al. (2015) and Batten et al. (2019) that oil price changes impact equity returns through the risk premium channel, it could be contended that investors' risk preferences influenced by shocks in the oil market contribute to fluctuations over time in the risk premiums linked to individual risk factors, which can be further magnified by the positive effect of oil market uncertainty on funding constraints (Christoffersen and Pan, 2018). At the same time, Chiah et al. (2022) argue that monetary policy adjustments to interest rates are more likely to occur during periods of high energy price volatility and these discount rate effects contribute to the appeal of bonds over stocks, potentially trickling down to a risk premium embedded in stock returns depending on the firm characteristics. From an investment perspective, if there is indeed a predictive relationship between oil market shocks and factor returns, such an effect holds substantial significance for the execution of smart beta strategies. These strategies capitalize on persistent trends in stock returns linked to firm characteristics, allowing the design of conditional factor portfolios based on these predictability patterns. The analysis also has implications for asset pricing as the disaggregated oil market shocks could be a source of systematic mispricing in financial markets, depending on the nature of the shock, which in turn can provide new insight into the time variation in stock market anomalies as factors can also be considered deviations from the efficient market hypothesis.

The literature on the relationship between oil and the stock market provides very limited evidence regarding the influence of oil price fluctuations on the systematic risk premia inherent in stock valuations. Although earlier works have established a clear link between unexpected changes in oil prices and the volatility of macroeconomic and financial factors (Park and Ratti, 2008) as well as macroeconomic uncertainty (e.g. Sheng et al., 2020), the effect of these shocks on the systematic risk premia in equity markets is relatively understudied. One argument in this regard is that oil price fluctuations can affect investors' expectations on inflation and real interest rates, thus opening a channel to expected firm cash flows and expected returns. Oil shocks can also affect consumption and investment decisions of economic agents, which in turn can affect risk attitudes by decision makers and funding conditions for firms (Prodromou and Demirer, 2022). Indeed, at the firm-level, a separate strand of the literature shows that oil market uncertainty can have a significant effect on corporate investment behavior (e.g. Maghyereh and Abdoh, 2020), while Ilyas et al. (2021) demonstrate that uncertainty in the oil market is related to economic policy uncertainty, influencing corporate investments.

This assertion is additionally corroborated by the findings of Yin and Lu (2022), indicating that heightened uncertainty in the oil market prompts firms to engage in greater risk-taking through mechanisms such as risk compensation or real options linked to the growth prospects of the companies. In contrast, Prodromou and Demirer (2022) contend that shocks in oil prices elevate the financing costs for firms through the liquidity channel. Indeed, Chiah et al. (2022) establish a connection between uncertainty in energy prices and the risk premium associated with how value stocks perform with respect to growth stocks. They posit that during periods when uncertainty regarding energy prices is high, value firms face greater challenges in adjustment due to their possession of a larger quantity of inflexible assets compared to growth firms and this inflexibility in firm operations in response to market shocks materializes itself in the form a risk premium associated with value firms. Overall, the evidence available in the literature provides a strong basis for us to study whether the time variation in factor returns can be explained by oil market shocks.

This paper makes several important contributions to the existing body of knowledge, particularly from the perspective of the oil-stock market nexus. First, it establishes a significant link between economic shocks, proxied by disentangled oil market shocks, and time-varying factor returns, an area that has been largely underexplored in asset pricing literature. By decomposing oil market shocks into components related to supply, demand, and economic activity, we provide a deeper understanding of how different types of oil shocks impact factor premiums across 62 global stock markets. Second, our study highlights the heterogeneous responses of factor

[2] Some of the prominent studies in this line of work include Cochrane (1996), Carlson et al., (2004), Zhang (2005), Belo (2010), Liu et al., (2009), Cooper and Priestly (2008, 2011) and Hou et al. (2015).

returns to oil price shocks across the developed and emerging markets, offering new insights into risk-return dynamics across these diverse economic contexts. This is also important given the popularity of factor investing strategies that exploit predictable patterns in stock returns. Third, we introduce a forward-looking investment strategy that leverages predictive insights from oil price fluctuations, leading to substantial improvements in risk-adjusted returns from factor-based portfolios. These contributions not only enhance the understanding of the stock market-oil nexus and its impact on equity factors, but also provide practical guidance for fund managers seeking to optimize their investments by incorporating macroeconomic variables.

Looking ahead, our findings show that oil market shocks indeed capture significant predictive information regarding the size and direction of factor returns in global stock markets although we observe a great deal of heterogeneity in the response of factor returns to disaggregated oil price shocks, depending on the stock market classification and the type of oil shock. In general, oil supply and precautionary demand shocks are found to possess the greatest predictive power over factor returns, particularly on value and momentum in global stock markets although factor returns in emerging stock markets display markedly different responses to oil price shocks compared to developed stock markets. We find that economic activity shocks positively predict the value premium in advanced markets, whereas oil consumption demand shocks positively predict value in both the advanced and developing stock markets. Similarly, while precautionary demand shocks and oil supply shocks resulting from production disruptions negatively affect momentum in developed markets, these shocks are found to drive up the value premium in these countries, highlighting the informational value of these shocks regarding market uncertainty and risk preferences. From an investment perspective, asymmetries in the response of factors to oil market shocks in developed versus emerging stock markets imply significant hedging potential for global investors by timing their factor investments based on shocks emanating from the oil market.

In our discussion of the findings, we provide several explanations to the heterogeneity in the responses of factor premia to oil price shocks across the different country groups using the evidence from the literature that links oil price shocks to financial stress, economic uncertainty and investors' risk perception. For example, comparing the results for major importing and exporting nations, we find that while oil demand shocks serve as the main driver of risk premia in these markets, these shocks have opposite effects on the two country groups with oil demand shocks positively (negatively) predicting factor returns in importing (exporting) nations. These contrasting results are explained using the evidence from the oil-stock market literature on how oil producers and consumers respond to good and bad energy market uncertainty. Overall, our findings present strong evidence of predictability running from disaggregated oil price shocks to factor returns with quite heterogeneous responses observed across the different country classifications and oil shock types. We argue that these heterogeneous patterns can be explained with time varying risk sentiment and firms' flexibility to respond to economic shocks, in line with the investment-based theories of asset pricing.

Further examining the economic implications of the predictive patterns observed, we show that investors can exploit the predictive relationship between oil market shocks and factor returns in an active setting to improve the risk and return profile of their portfolios. Proposing a forward-looking, global factor investing strategy wherein the investment positions switch between the passive and active factor positions conditioned on the size and direction of the oil market shock, we document significant improvements in the risk and return profile of investment portfolios over the passive investment strategy, particularly when the strategy is conditioned on supply and economic activity shocks. Finally, motivated by the evidence in the literature of asymmetries in the effect of energy price uncertainty on stock returns, we show that tilting the portfolio towards momentum following large positive supply shocks can help double the risk-adjusted returns, while exploiting momentum against negative precautionary demand shocks can further improve risk-adjusted returns coupled with almost 25 % reduction in portfolio risk. Overall, our findings highlight the predictive role of oil market shocks on global risk premia and show that the performance of smart beta strategies can be improved by exploiting the predictive power of oil market shocks over global factor returns in a dynamic setting.

The remainder of this paper is organized as follows. Section 2 presents a brief review of the growing literature on the nexus between oil market shocks, stock returns and systematic risk premia. Section 3 describes methodology and the data used in our empirical analysis. Section 4 presents the empirical findings from the time-varying causality tests and cross-sectional regressions as well as the economic implications of our findings. Finally, Section 5 concludes with suggestions for future extensions of our research.

2. Literature review

The precursor works by Kilian (2009) and Kilian and Park (2009) have steered the extensive body of literature on the link between oil and the stock market in a new direction. These studies contend that neglecting the source of oil price shocks in the analysis may lead to a bias towards detecting a predominantly insignificant effect that lacks stability over time. Consequently, Kilian (2009) introduces a methodological approach, utilizing a structural vector autoregressive model of crude oil prices, to break down oil prices into components reflecting global demand fluctuations, unexpected shifts in world petroleum production, and rises in precautionary demand stemming from concerns about potential shortages in future oil supply. Kilian and Park (2009) subsequently demonstrate that the impact of oil prices on the stock market is primarily influenced by factors related to oil demand rather than supply. Moreover, they assert that the impact of oil demand shocks is contingent upon the nature of the shock, specifically when the fluctuations in oil prices stem from precautionary or aggregate demand shocks. The findings from the Kilian-Park studies have later prompted a multitude of investigations exploring the influence of oil price shocks on financial markets. Numerous applications to diverse stock markets, as seen in the works of Apergis and Miller (2009), Basher et al. (2012), Filis et al. (2011), Güntner (2014), Kang et al. (2015), Wang et al. (2013), Basher et al. (2018), Salisu et al. (2022), and others, consistently underscore the predominant role of demand shocks in shaping stock market dynamics, while Demirer et al. (2020) observe a similar effect on global bond markets.

In addition to evaluating the repercussions of oil price shocks on financial market returns, another strand of research has delved into examining the impact of these shocks on market uncertainty. While studies such as Kang and Ratti (2013a), (2013b) and Kang et al. (2015) report favorable responses of uncertainty to demand shocks specific to the oil market, Antonakakis et al. (2014) present a contrasting argument, failing to identify a substantial impact of uncertainty on consumption demand shocks. This aligns with the heterogeneous effects of oil price shocks on economic uncertainty highlighted in the works of studies including Hailemariam et al. (2019) and Degiannakis et al. (2018). On a different note, Kang et al. (2017) and Su et al. (2018) propose that disruptions on the supply side can impact uncertainty, while Sheng et al. (2020) show that uncertainty is significantly influenced by both oil supply and demand shocks. However, these effects are contingent on the prevailing regime, intertwined with the state of investor sentiment and risk perception, as evidenced by Sheng et al. (2020). Recent support for these findings comes from Dagher and Hasanov (2023), who reveal an asymmetric impact of oil shocks on financial stability in Asian countries. They observe that oil price increases resulting from oil-specific demand shocks tend to alleviate stress in financial markets, while increases in oil prices due to oil-specific supply shocks lead to heightened financial market stress.

Despite the extensive body of literature examining the impact of shocks in the oil market on financial market returns and uncertainty, the role of these shocks in predicting the risk premiums linked to persistent patterns in stock market returns has been relatively overlooked, with few exceptions. The existing evidence generally report some degree of predictive link between oil market volatility and payoffs in equity market momentum (Chen et al., 2017) and investor sentiment (Ding et al., 2017). Similarly, Cheema and Scrimgeour (2019) document the effects of oil prices on mispricing patterns in stock returns, but their focus is exclusively on the Chinese equity market, limiting the generalizability of their findings. Expanding this research to encompass the U.S. oil and gas industry, Zhu et al. (2020) reveal that six out of fifteen anomalies are significantly influenced by aggregate oil price shocks. In a similar vein, Kumar et al. (2020) present evidence of directional predictability to forecast the direction of systematic risk premiums, particularly those linked to size and momentum factors, based on oil returns. Nonetheless, their analysis does not extend to the examination of disaggregated oil price shocks. In an application to the U.S. stock market that is more closely aligned with our analysis, Zhu et al. (2022) show that aggregate demand shocks are the dominant drivers of stock market anomalies in the U.S., particularly for small firms with high idiosyncratic volatility. Similarly, focusing on the U.S. stock market, Chiah et al. (2022) document a positive relationship between the value premium in stock returns and uncertainty in energy prices and, once again without distinguishing between the nature of oil market shocks.

Against this backdrop, our work builds on the asset pricing and oil-stock market literatures by focusing on the forecasting power of disaggregated oil price shocks over the risk premia linked to the systematic risk factors that form the foundation for factor investing strategies. This holds significance not only from an investment standpoint, as detailed examination of disentangled shocks in the oil market can encapsulate valuable insights into the diverse facets of economic uncertainty and investor risk perceptions, but it also has the potential to provide innovative perspectives on the relationship between the oil and the stock markets. This is achieved by exploring the possible connections between shocks in the oil market and systematic mispricing observed in stock markets. In that regard, our study extends the literature in a novel direction by analysing the predictive effect of oil price shocks on factor returns in a large number of global stock markets and whether or not such a predictive relationship can be used in conditional factor strategies, which is an important consideration for the rapidly growing managed funds industry that adopts a factor-based approach in their investments.

3. Data and methodology

3.1. Data

Our study employs monthly data pertaining to risk premia in stock markets across 62 countries, as outlined in Table A1 in the Appendix. Additionally, it incorporates a series of oil price shocks designed to encompass shocks related to oil supply, consumption demand, inventory (precautionary) demand and economic activity related factors. Table 1 presents the initiation dates for each country series, all concluding in December 2022. Note that the time horizon of the dataset is selected based on the availability of data at the time of conducting the analysis.

The computation of oil price shocks adheres to the methodology introduced by Baumeister and Hamilton (2019). This method considers the volume of worldwide crude oil production, economic output, the real oil price, and global inventory of crude oil to encompass diverse shocks within the oil market. To break down these shocks into distinct components, the authors use a structural Bayesian vector autoregressive (SBVAR) framework, where real oil prices are modeled against the production of world crude oil (oil supply proxy), the OECD-wide industrial production index (real economic activity proxy), and the product of U.S. crude oil stocks multiplied by the proportion of the petroleum inventory of the OECD to that of the U.S. (estimation of crude oil inventories). This modeling results in the derivation of oil market shock series disentangled into four constituents that are associated with supply (OSS), consumption demand (OCDS), (precautionary) inventory demand (OIDS) and economic activity (EAS) shocks.[3]

The construction of the stock market premium series follows Jensen et al. (2023) who propose a Bayesian model to assess factor replicability across a large number of global stock markets. In this procedure, stocks in each country are sorted into characteristic terciles each month where stocks are sorted into three groups of equal numbers of stocks based on the characteristic that represents a given factor. For each tercile, stocks are weighted by their market capitalization values, yielding portfolios sorted on firm characteristics. The factor is then computed as the difference between the returns for the highest and lowest tercile portfolios which captures

[3] Data accessible at https://sites.google.com/site/cjsbaumeister/research

Table 1
. Summary statistics.

	N	Mean	S.D	Min	Max	Sample period
	Panel A: Size					
Developed Markets	429	0.173	1.433	−4.929	5.846	Apr−86
Emerging Markets	395	0.309	2.690	−24.952	14.502	Feb−89
Frontier Markets	183	−0.013	1.706	−5.343	4.246	Oct−06
BRICS	421	0.414	2.616	−9.863	18.154	Dec−86
Oil Exporters	476	0.079	2.157	−25.520	13.563	May−82
Oil Importers	563	0.285	1.675	−7.372	7.128	Feb−75
	Panel B: Value					
Developed Markets	429	0.332	1.869	−12.96	9.735	Apr−86
Emerging Markets	395	0.372	1.940	−8.843	19.147	Feb−89
Frontier Markets	183	0.313	1.404	−2.865	6.289	Oct−06
BRICS	421	0.584	2.371	−9.108	9.821	Dec−86
Oil Exporters	476	0.498	2.318	−7.567	30.418	May−82
Oil Importers	563	0.377	2.078	−14.475	9.600	Feb−75
	Panel C: Momentum					
Developed Markets	429	0.304	2.594	−14.722	12.250	Apr−86
Emerging Markets	395	0.320	2.453	−20.876	9.863	Feb−89
Frontier Markets	183	0.681	2.209	−9.900	7.251	Oct−06
BRICS	421	0.417	3.173	−16.497	10.748	Dec−86
Oil Exporters	476	0.403	2.812	−25.196	7.676	May−82
Oil Importers	563	0.265	2.449	−12.821	11.755	Feb−75
	Panel D: Oil Shocks					
Supply (OSS)	563	−0.037	1.575	−10.747	4.709	
Economic Activity (EAS)	563	−0.011	o.683	−7.045	3.579	
Demand (OCDS)	563	−0.134	3.711	−20.970	10.628	
Inventory (OIDS)	563	0.020	1.095	−3.043	4.315	

Note: This table presents the descriptive statistics for the monthly risk premia and oil shock series. The last column shows the start date for each country group with a common ending date for all in December 2022. OSS: oil supply shock; EAS: economic activity shock; OCDS: oil-specific consumption demand shock; OIDS: oil inventory demand shock.

the excess return associated with the exposure to the given factor.[4] In our application, following the well-established evidence that supports a three-factor model in equity returns (e.g. Fama and French, 1993, 1996; Jegadeesh and Titman, 1993; Carhart, 1997), we focus our analysis on the predictability of the size, value and momentum premia that reflect the excess returns obtained from a long-short portfolio of small minus big, value minus growth and past winner minus past loser stocks. This also allows us to better relate our findings to a practical economic context as these factors represent some of the most popular characteristic-managed portfolios in the managed fund industry.

Table 1 presents the summary statistics for the monthly risk premia and oil shock series. Given the large number of countries in our sample, in addition to country-level tests, we perform our tests on various country groups as shown in Table A1 in the Appendix. As presented in Table 1, we observe a great deal of heterogeneity in factor returns across the country groups. While BRICS stock markets yield the highest excess returns corresponding to firm size and value with 0.414 % and 0.584 % per month, respectively, momentum seems to yield the largest reward in frontier stock markets along with BRICS. However, relatively higher returns from the momentum strategy are coupled with higher volatility compared to the size and value-based portfolios. Finally, all oil shock series experience negative mean values during the sample period, likely due to the inclusion of long periods of oil market slumps as a result of the global slowdowns observed throughout much of the sample period.

3.2. Methodology

3.2.1. Modeling time-varying causality

In our analysis, we employ the time-varying Granger causality approach introduced in Shi et al. (2018), (2020) to examine the causal flow from oil price shocks to each risk premium series within various country groups. This method has some specific advantages. First, instead of assessing an average causal effect for the whole time period of the sample, it captures the dynamic changes in causality over time, thus providing a more accurate assessment of how oil price shocks impact factor returns in our case. Second, this approach does not require prefiltering the series to eliminate non-stationarity. Third, this approach facilitates multiple configurations of cointegrated, non-stationary and stationary series in its modeling framework, while it can be applied to deterministically trending and integrated variables. Finally, it allows to investigate the robustness of the detected causal relationships given its dynamic setting.

Consider an n-vector variable z_t generated by

$$z_t = a_0 + a_1 t + e_t \tag{1}$$

[4] Country-level factor data available at Bryan Kelly's global factor data page: https://jkpfactors.com/

where e_t follows a VAR(q) process in the form

$$e_t = b_1 \quad e_{t-1} + \ldots \quad + b_q \quad e_{t-q} + \mu_t \tag{2}$$

and μ_t is the error term. Substituting $e_t = z_t - (a_0 + a_1 t)$ in Eq. (1) into Eq. (2) yields

$$z_t = g_0 + g_1 t + b_1 \quad z_{t-1} + \ldots + b_q \quad z_{t-q} + \mu_t \tag{3}$$

where g_i is a function of a_i and b_j with $j = 1,\ldots,q$ and $i = 0$ and 1.

Considering an n-dimensional vector z_t, the lag-augmented VAR model is then written as

$$Z = S\Psi' + X\Phi' + \tau\Gamma' + \mu \tag{4}$$

where $Z = (z_1, z_2, \ldots, z_T)'_{T\times n}$, $S = (s_1, \ldots, s_T)'_{T\times nd}$, $X = (x_1, \ldots, x_T)'_{T\times nk}$, $\tau = (\tau_1, \ldots, \tau_T)'_{T\times 2}$ and $\mu = (\mu_1, \ldots, \mu_T)'_{T\times n}$. In this setting, d represents the maximum order of integration of z_t. The OLS estimator is then defined as

$$\widehat{\Phi} = Z'QX(X'QX)^{-1} \tag{5}$$

and the causal flow between variables is tested using the standard Wald statistic formulated as

$$W = (\rho\widehat{F})'[\rho(\widehat{\Sigma}_\varepsilon \otimes (X'QX)^{-1})\rho']^{-1}\rho\widehat{F} \tag{6}$$

where $\otimes$ is the Kronecker product, $\widehat{\Sigma}_\varepsilon = \frac{1}{T}\widehat{\varepsilon}'\widehat{\varepsilon}$, $\widehat{F} = vec(\widehat{\Phi})$, ρ is a $m \times n^2 q$ matrix, with m indicating the number of restrictions. Under the null of $H_0 : \rho F = 0$ and assuming conditional homoscedasticity, the Wald statistic W has a standard χ^2_m asymptotic null distribution.

Shi et al. (2018), (2020) propose several alternative causal algorithms to capture time-varying causal interactions, namely forward recursive causality, recursive evolving causality, and rolling causality. According to their results, the comparative analysis of these algorithms show that the recursive evolving window algorithm yields the most accurate assessment compared to the other methods and in our application, we adopt this approach. In the recursive evolving window procedure, a sequence of Wald statistics $\{W_{j_1,j_2}\}_{j_2=j}^{j_1\in[0,\, j_2-j_0]}$ can be obtained for each observation j via the test statistic in Eq. (7) which is the supremum of the Wald statistic sequence formulated as

$$SW_j(j_0) = \sup_{j_2=j, j_1\in[0, j_2-j_0]} \{W_{j_1,j_2}\} \tag{7}$$

for some minimal sample size $j_0 \in [0, 1]$. The recursive evolving algorithm is then used to identify switch dates that define the direction of causality based on critical values of the W_j and SW_j statistics by identifying the first chronological observation for which the test statistic exceeds or falls below the critical values. Finally, the optimal lag length in each VAR model is determined by the Akaike information criterion.

3.2.2. *Cross-sectional analysis*

After assessing the dynamic causality links between oil price shocks and factor returns, in the next step, cross-sectional regressions are used to explore the influence of oil price shocks on each factor return series across different country groups This allows us to quantify the predictive direction and size of each shock on factor returns, which is an important consideration for our subsequent analysis of the economic implications of our findings. To that end, we estimate two alternative predictive models in the form

$$RP_{i,t} = \alpha_0 + \quad \alpha_1 OSS_{t-1} + \quad \alpha_2 EAS_{t-1} \quad + \quad \alpha_3 OCDS_{t-1} + \quad \alpha_4 OIDS_{t-1} + \varepsilon_{i,t} \tag{8}$$

$$RP_{i,t} = \alpha_0 + \quad \alpha_1 RP_{i,t-1} + \quad \alpha_2 OSS_{t-1} + \quad \alpha_3 EAS_{t-1} \quad + \quad \alpha_4 OCDS_{t-1} + \quad \alpha_5 OIDS_{t-1} + \varepsilon_{i,t} \tag{9}$$

where $RP_{i,t}$ is the risk premium in month t for country i. As described earlier, we are interested in predictive role of oil price shocks and so include in the model lagged oil price shocks associated with supply, consumption demand, precautionary (inventory) demand and economic activity related factors, represented by OSS, OCDS, OIDS, EAS respectively, as predictors. Eqs. 8 and 9 are estimated for each factor (size, value, momentum) separately one at a time for each country group by controlling for country effects.

3.2.3. *Portfolio analysis*

In order to provide an economic insight to our predictive analysis of oil market shocks and factor returns, we conduct a portfolio analysis by considering a naive investor who currently holds a position in the aggregate stock market index and propose a dynamic investment strategy where the investor augments the passive index portfolio with each of the factors (size, value, and momentum) one at a time, conditional on the size and direction of oil market shocks as explained in further detail in our discussion of the economic implications. Specifically, we estimate optimal portfolio allocation by implementing the mean-variance approximations to expected utility analysis of Markowitz (2014). In the portfolio optimization problem setting, we consider a set of n assets denoted by $A = \{a_1, a_2, \ldots a_n\}$ where each asset a_i is characterized by an expected return r_i and the covariance between two assets a_i and a_j $(\forall i, j \epsilon \{1, 2, \ldots n\})$ is represented by σ_{ij}. A solution to the optimization problem can be encoded as a vector $X = \{x_1, x_2, \ldots x_n\}$ where each element $x_i(\{0 \leq x_i \leq 1\})$ represents the weight of the investment allocated to the asset a_i. The constrained portfolio optimization problem can then mathematically be described as:

$$\min f(x) = \sum_{i=1}^{n} \sum_{j=1}^{n} \sigma_{ij} x_i x_j \tag{10}$$

subject to

$$\sum_{i=1}^{n} r_i x_i \geq R \text{and} \sum_{i=1}^{n} x_i = 1 \tag{11}$$

with $z_i \epsilon \{0, 1\}$, $\forall i \epsilon \{1, 2, \ldots, n\}$, $x_i \leq z_i$, $\forall i \epsilon \{1, 2, \ldots, n\}$ ensuring that if x_i is greater than 0, then z_i is 1, and $\varepsilon_i z_i \leq x_i \leq \delta_i z_i$, $\forall i \epsilon \{1, 2, \ldots, n\}$, setting lower and upper bounds (ε_i and δ_i, respectively) for x_i in case the asset is included in the portfolio. In this formulation, the optimal portfolio allocations are obtained by minimizing portfolio risk given that the expected portfolio return does

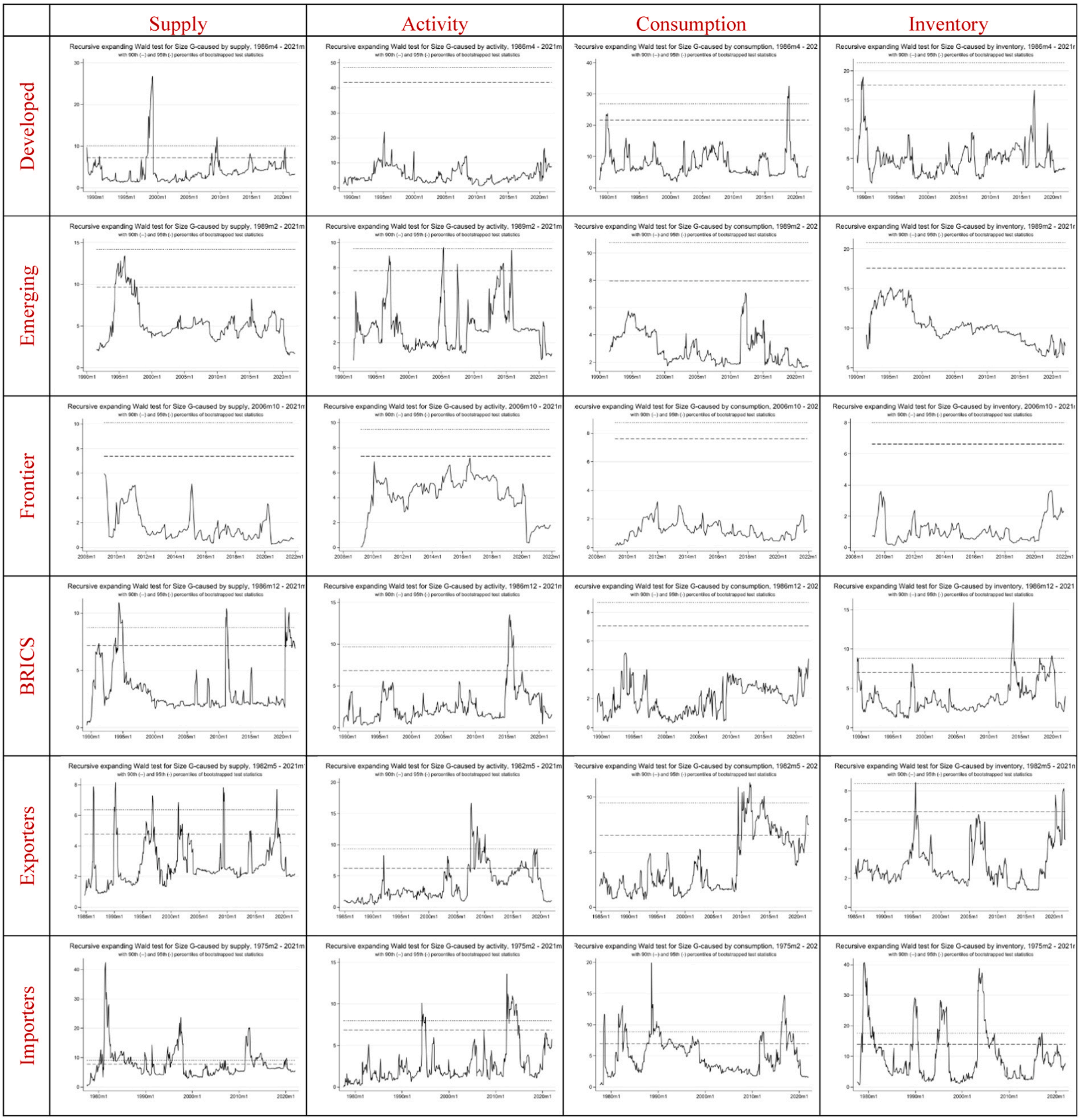

Fig. 1. Causality from oil price shocks to the *Size premia* in world markets. **Note:** The figures present the Wald test statistics for time-varying causality running from each type of oil shock to excess returns for the Size factor based on the recursive evolving window algorithm of Shi et al. (2018), (2020). The 90th and 95th percentiles of the bootstrapped test statistics are shown in dashed lines.

not fall below the target return R and whether or not asset a_i is included in the optimal portfolio is represented by means of the auxiliary variable z_i ($z_i = 1$ if positive; zero otherwise), thus confining the weights assigned to assets in the portfolio within a floor and a ceiling. To solve the optimization problem, we implement DEoptim: Global Optimization by Differential Evolution (Mullen et al., 2011) solver with 2000 iterations.

4. Empirical results

4.1. *Dynamic causal relationships*

Before we proceed with our discussion of the time-varying causality tests, we first report in Table A2 (Appendix) the p-values obtained from the standard linear Granger causality tests running from each oil shock series to excess returns associated with the size,

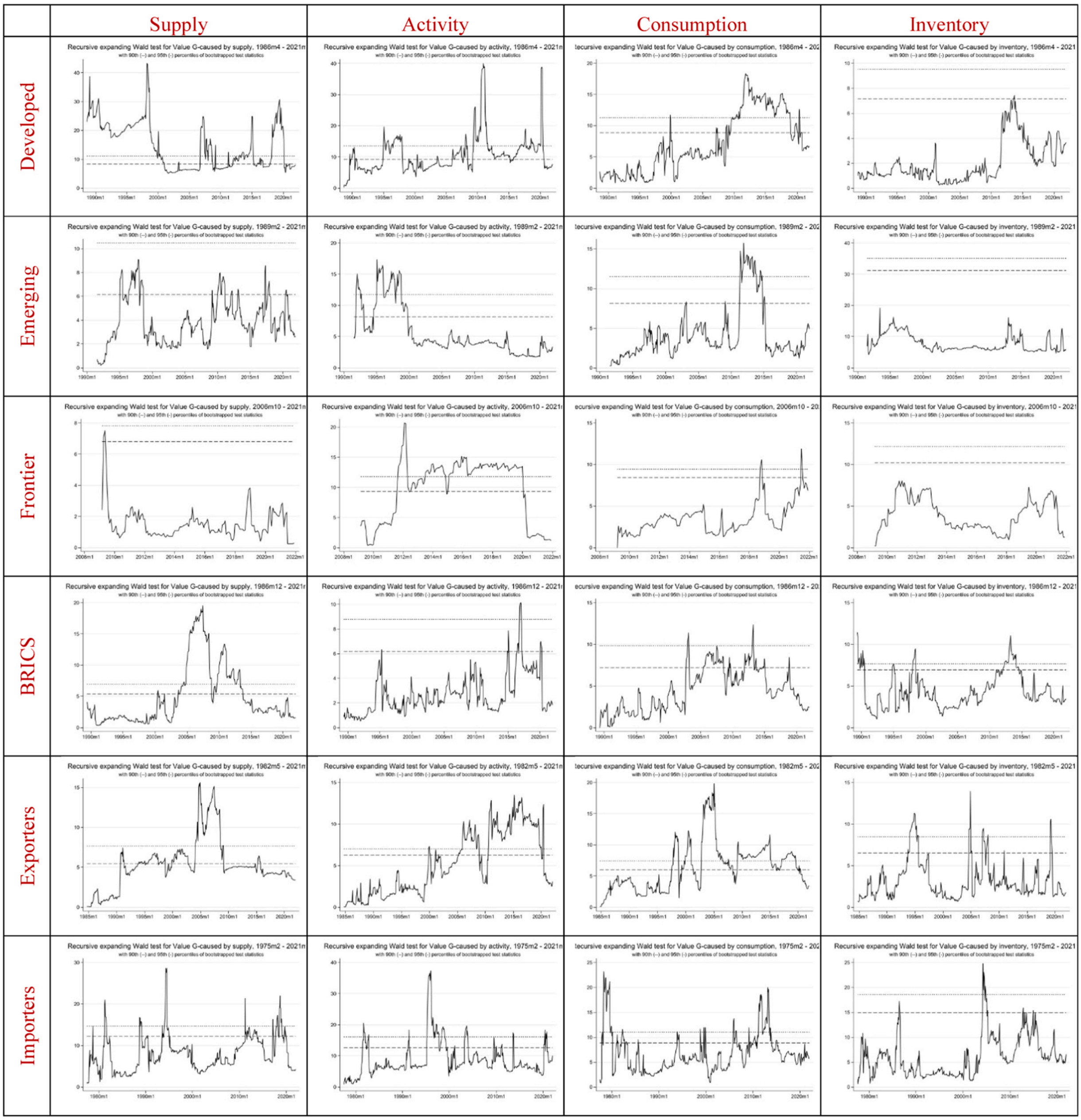

Fig. 2. Causality from oil price shocks to the *Value premia* in world markets. **Note:** The figures present the Wald test statistics for time-varying causality running from each type of oil shock to excess returns for the Value factor based on the recursive evolving window algorithm of Shi et al. (2018), (2020). The 90th and 95th percentiles of the bootstrapped test statistics are shown in dashed lines.

value and momentum factors (in Panels A, B and C, respectively) for the country groups listed in Table A1 in the Appendix. We observe that the standard linear tests generally fail to capture any significant causal effects indicated by insignificant results for most cases. The only exceptions are the significant causality found from oil inventory demand shocks to the size and value premia in emerging stock markets as well as momentum in frontier stock markets. We also observe several other significant causal effects of oil supply shocks on momentum returns in the developed and emerging stock markets as well as major commodity exporters. In a recent study, Dagher and Hasanov (2023) document a positive association between financial market stress and oil price increases driven by oil-specific supply shocks and this could be a factor driving the significant causality that we observe in Table A2 from oil supply shocks to momentum returns as momentum is shown to be highly sensitive to market volatility (Wang and Xu, 2015; Chen et al., 2017). From another perspective, Demirer and Jategaonkar (2020) find that increased risk aversion anticipates diminished momentum returns in stock markets, thus the causal effects of supply shocks could be a manifestation of the effect of market uncertainty induced by oil market disruptions on risk preferences among investors, which aligns with the findings by Daniel and Moskowitz (2016) of instances of

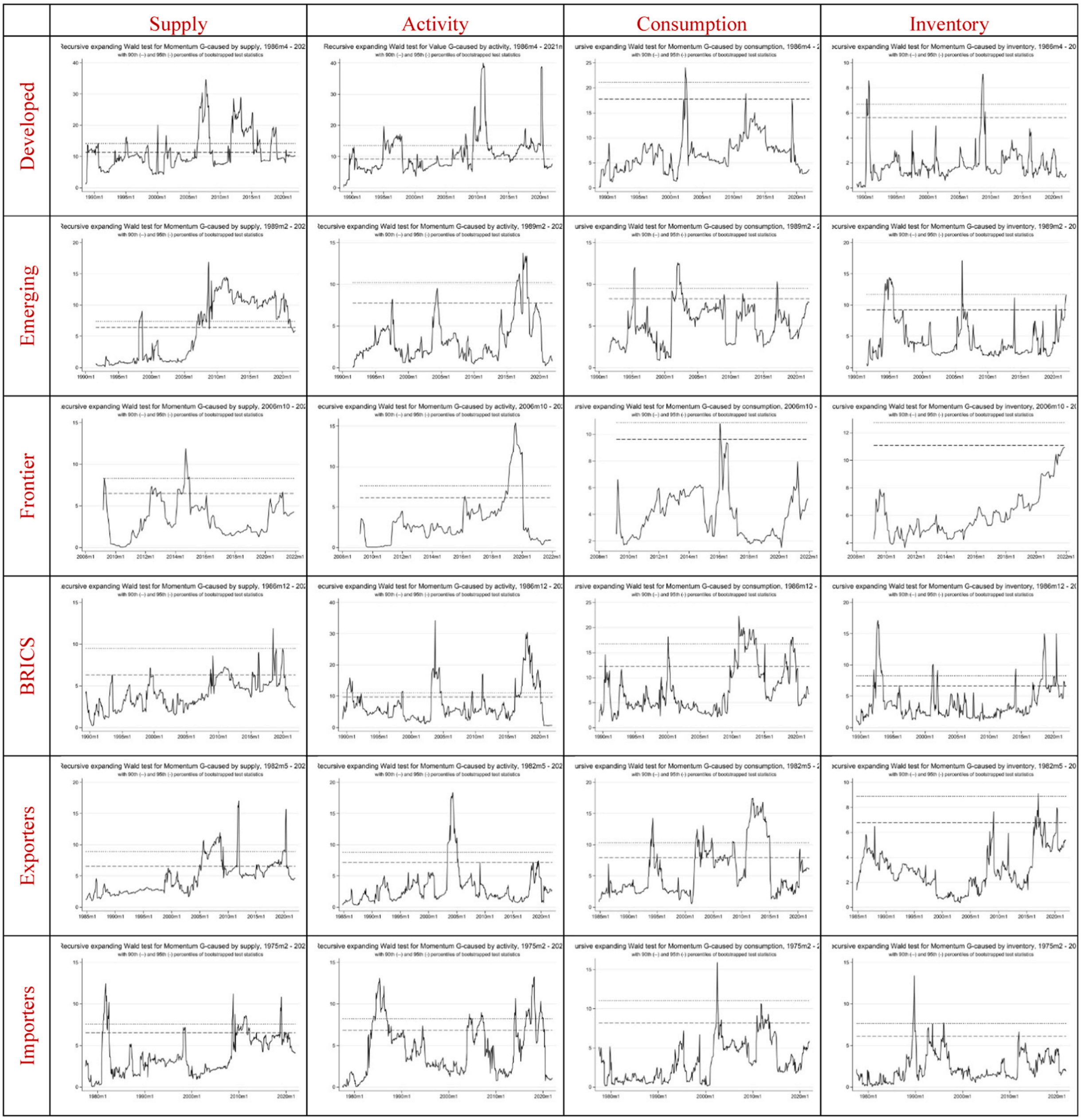

Fig. 3. Causality from oil price shocks to the *Momentum premia* in world markets. **Note:** The figures present the Wald test statistics for time-varying causality running from each type of oil shock to excess returns for the Momentum factor based on the recursive evolving window algorithm of Shi et al. (2018), (2020). The 90th and 95th percentiles of the bootstrapped test statistics are shown in dashed lines.

momentum crashes taking place amid elevated volatility states subsequent to market downturns.

Figs. 1 to 3 present the Wald test statistics for time-varying causality running from each type of oil shock to factor returns associated with size, value and momentum respectively, based on the recursive evolving window algorithm of Shi et al. (2018), (2020). The 90th and 95th percentiles of the bootstrapped test statistics are shown in dashed lines. The results for size in Fig. 1 yield largely insignificant effects, consistent with the findings from the linear causality tests in Table A2, although we observe several episodes when the causal effects of oil supply shocks turn significant such as the mid to late 1990s during which we generally observe positive oil supply shocks, supporting the evidence by Dagher and Hasanov (2023) of higher market stress in response to oil price increases due to oil-specific supply shocks. Interestingly, the effect of oil price shocks on the size premia is found to be particularly strong for major commodity importers with significant causality observed from both the supply and demand driven shocks during mid to early 1990s as well as during the latter part of the sample following the global financial crash of 2007/2008. In the case of commodity exporters, we find that both the oil consumption and inventory demand shocks drive size premia in these countries and that the causal effects seem to have strengthened following the COVID-19 pandemic in 2020. Sheng et al. (2020) show that shocks specific to the oil market's demand (i.e., consumption) exert a notable influence on macroeconomic uncertainty over the medium to long term. Consequently, it can be asserted that oil demand shocks assumed a prominent predictive role in relation to economic fundamentals during the COVID-19 pandemic. This, in turn, resulted in substantial causation of risk premia on small-cap stocks observed in exporting economies.

Table 2

Cross-sectional regression results for country groups − *Size*.

	Developed Markets		Emerging Markets	
	Model 1	Model 2	Model 1	Model 2
α	0.041	0.040	0.672***	0.671***
	(1.359)	(1.307)	(7.582)	(7.562)
$Size_{i,t-1}$		0.034***		0.007
		(3.381)		(0.596)
$OSS_{i,t-1}$	−0.015	−0.014	2.573***	2.57***
	(−0.619)	(−0.566)	(6.672)	(6.665)
$EAS_{i,t-1}$	0.145***	0.147***	1.066	1.055
	(3.35)	(3.398)	(1.168)	(1.156)
$OCDS_{i,t-1}$	−0.005	−0.007	−0.164	−0.163
	(−0.602)	(−0.789)	(−1.172)	(−1.164)
$OIDS_{i,t-1}$	0.021	0.016	2.435***	2.438***
	(0.681)	(0.517)	(4.503)	(4.508)
R-sq	0.003	0.004	0.100	0.100
	Frontier Markets		BRICS	
	Model 1	Model 2	Model 1	Model 2
α	−0.068	−0.067	0.291***	0.266**
	(−0.484)	(−0.476)	(2.689)	(2.462)
$Size_{i,t-1}$		−0.026		0.077***
		(−0.727)		(3.267)
$OSS_{i,t-1}$	0.074	0.082	−0.040	−0.048
	(0.193)	(0.213)	(−0.425)	(−0.504)
$EAS_{i,t-1}$	−0.304	−0.302	0.075	0.077
	(−0.742)	(−0.736)	(0.51)	(0.525)
$OCDS_{i,t-1}$	−0.081	−0.077	0.024	0.024
	(−0.64)	(−0.61)	(0.749)	(0.724)
$OIDS_{i,t-1}$	−0.93**	−0.938**	−0.039	−0.044
	(−1.999)	(−2.016)	(−0.355)	(−0.401)
R-sq	0.226	0.227	0.003	0.009
	Exporter		Importer	
	Model 1	Model 2	Model 1	Model 2
α	−0.144	−0.142	0.230***	0.204***
	(−1.126)	(−1.111)	(3.365)	(2.998)
$Size_{i,t-1}$		0.021		0.110***
		(1.177)		(5.582)
$OSS_{i,t-1}$	−0.77	−0.754	0.012	0.006
	(−0.914)	(−0.895)	(0.224)	(0.120)
$EAS_{i,t-1}$	−0.573	−0.555	0.026	0.036
	(−1.115)	(−1.08)	(0.276)	(0.379)
$OCDS_{i,t-1}$	−0.343*	−0.345*	0.023	0.019
	(−1.719)	(−1.727)	(1.13)	(0.935)
$OIDS_{i,t-1}$	−2.237***	−2.209***	0.129*	0.126*
	(−3.272)	(−3.229)	(1.879)	(1.836)
R-sq	0.172	0.172	0.004	0.016

Note: This table presents the estimates for Eq. 8 (Model 1) and Eq. 9 (Model 2) for the size factor, estimated cross-sectionally across country groups listed in Table A1 in the Appendix. OSS: oil supply shock; EAS: economic activity shock; OCDS: oil-specific consumption demand shock; OIDS: oil inventory demand shock. *t* statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Extending the analysis to the value premia, the results presented in Fig. 2 indicate strong causal effects from supply shocks to the value factor returns in developed and emerging stock markets during much of the 1990s when the new economy stocks took financial markets by storm as investors' risk-taking behavior peaked towards growth stocks. Considering the evidence by Sheng et al. (2020) of a positive association between macroeconomic uncertainty and oil supply shocks, particularly during high-volatility periods, and the finding by Chiah et al. (2022) of a positive relationship between energy price uncertainty and the value premium, it can be argued that supply shocks captured an element of economic uncertainty during this period related to the ability of firms with large amount of inflexible assets to adjust to market changes, thus establishing a predictive relationship to excess returns on value firms. In the latter part of the sample, however, we observe the causal effect of oil shocks on the value premium shifts towards oil consumption demand shocks, particularly during the aftermath of the global financial crisis and the Eurozone financial crisis. Considering the finding by Lettau and Wachter (2007) and Gormsen and Lazarus (2023) that links the value factor to discount rate shocks, it can be argued that oil market shocks associated with consumption demand captured uncertainty regarding monetary policy decisions and interest rate uncertainty, thus making consumption shocks the dominant driver of the value premium during this period. The significant causality on the value factor is observed in both the developed and emerging stock markets, suggesting that investors could have used disaggregated oil shocks to tilt their investment positions in these factors conditional on the nature of the shock.

Finally, the results for momentum presented in Fig. 3 show significant causal effects of supply and economic activity related shocks

Table 3
Cross-sectional regression results for country groups − *Value*.

	Developed Markets		Emerging Markets	
	Model 1	Model 2	Model 1	Model 2
α	0.275***	0.245***	0.436***	0.431***
	(8.767)	(7.834)	(9.574)	(9.421)
$Value_{i,t-1}$		0.113***		0.010
		(11.163)		(0.904)
$OSS_{i,t-1}$	0.107***	0.098***	0.095**	0.095**
	(4.166)	(3.846)	(2.324)	(2.315)
$EAS_{i,t-1}$	0.252***	0.251***	0.083	0.083
	(5.718)	(5.741)	(1.363)	(1.368)
$OCDS_{i,t-1}$	0.032***	0.027***	0.029**	0.029**
	(3.388)	(2.822)	(2.081)	(2.055)
$OIDS_{i,t-1}$	0.019	0.012	−0.005	−0.006
	(0.601)	(0.374)	(−0.104)	(−0.131)
R-sq	0.007	0.019	0.005	0.005
	Frontier Markets		BRICS	
	Model 1	Model 2	Model 1	Model 2
α	0.363***	0.350***	0.555***	0.524***
	(3.339)	(3.199)	(5.164)	(4.845)
$Value_{i,t-1}$		0.041		0.052**
		(1.349)		(2.177)
$OSS_{i,t-1}$	0.094	0.086	−0.006	−0.009
	(1.021)	(0.925)	(−0.066)	(−0.096)
$EAS_{i,t-1}$	0.074	0.073	−0.077	−0.075
	(0.618)	(0.606)	(−0.531)	(−0.52)
$OCDS_{i,t-1}$	0.026	0.023	−0.01	−0.011
	(0.836)	(0.719)	(−0.294)	(−0.343)
$OIDS_{i,t-1}$	0.182	0.179	−0.125	−0.135
	(1.591)	(1.568)	(−1.143)	(−1.234)
R-sq	0.011	0.012	0.008	0.011
	Exporters		Importers	
	Model 1	Model 2	Model 1	Model 2
α	0.331***	0.324***	0.346***	0.31***
	(2.718)	(2.648)	(5.004)	(4.487)
$Value_{i,t-1}$		0.012		0.115***
		(0.666)		(5.75)
$OSS_{i,t-1}$	−0.102	−0.109	0.105*	0.100*
	(−0.132)	(−0.141)	(1.937)	(1.851)
$EAS_{i,t-1}$	−0.939*	−0.94*	0.292***	0.302***
	(−1.954)	(−1.957)	(3.003)	(3.127)
$OCDS_{i,t-1}$	0.097	0.096	0.023	0.023
	(0.515)	(0.511)	(1.133)	(1.132)
$OIDS_{i,t-1}$	−1.311**	−1.322**	0.024	0.03
	(−1.99)	(−2.005)	(0.349)	(0.437)
R-sq	0.210	0.210	0.005	0.018

Note: This table presents the estimates for Eq. 8 (Model 1) and Eq. 9 (Model 2) for the value factor, estimated cross-sectionally across country groups listed in Table A1 in the Appendix. OSS: oil supply shock; EAS: economic activity shock; OCDS: oil-specific consumption demand shock; OIDS: oil inventory demand shock. *t* statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

on momentum in developed and emerging stocks markets, particularly after 2010 following the global financial crisis. Sheng et al. (2020) report an adverse effect of a shock to economic activity on economic uncertainty as a result of an upswing in global aggregate demand that fosters a favorable economic outlook. Therefore, considering the evidence in Berk et al. (1999) and Johnson (2002) who establish a link between the growth options of firms and the momentum factor, the causal effect of economic activity shocks on momentum could be a manifestation of investors' growth expectations captured by these shocks. In contrast, we observe largely insignificant effects in frontier stock markets, most likely as these markets lack sufficient market depth and instruments that will help achieve consistent returns from momentum-based strategies. Further distinguishing between commodity importers and exporters does not yield consistent causality patterns, likely due to the heterogeneity in the stock market characteristics involved within these country groups. Overall, the dynamic causality analysis shows that oil market shocks capture significant predictive information regarding the size and direction of factor returns in global stock markets although we observe a great deal of heterogeneity in the response of factor returns to these shocks, depending on the market classification and the type of oil shock. It must, however, be noted that the causality analysis presented so far does not help identify the magnitude and sign of the predictive effect of oil shocks. Thus, to enlarge our understanding of the predictive relationship between disaggregated oil shocks and factor returns, we next proceed with the cross-sectional analysis described in Section 3.2.2.

Table 4
Cross-sectional regression results for country groups – *Momentum*.

	Developed Markets		Emerging Markets	
	Model 1	Model 2	Model 1	Model 2
α	0.449***	0.428***	0.773***	0.767***
	(10.865)	(10.307)	(7.918)	(7.849)
$Momentum_{i,t-1}$		0.047***		0.015
		(4.645)		(1.365)
$OSS_{i,t-1}$	−0.141***	−0.137***	1.292***	1.297***
	(−4.288)	(−4.156)	(3.05)	(3.063)
$EAS_{i,t-1}$	−0.287***	−0.290***	2.345**	2.369**
	(−4.932)	(−4.976)	(2.408)	(2.433)
$OCDS_{i,t-1}$	0.001	0.002	0.027	0.026
	(0.019)	(0.188)	(0.167)	(0.158)
$OIDS_{i,t-1}$	−0.094**	−0.083**	1.806***	1.795***
	(−2.258)	(−1.987)	(3.097)	(3.079)
R-sq	0.007	0.009	0.168	0.168
	Frontier Markets		BRICS	
	Model 1	Model 2	Model 1	Model 2
α	0.484***	0.438***	0.458***	0.399***
	(3.457)	(3.111)	(3.406)	(2.984)
$Momentum_{i,t-1}$		0.079***		0.134***
		(2.624)		(5.7)
$OSS_{i,t-1}$	−0.350***	−0.361***	−0.058	−0.048
	(−2.947)	(−3.044)	(−0.494)	(−0.411)
$EAS_{i,t-1}$	−0.135	−0.137	0.06	0.071
	(−0.871)	(−0.885)	(0.331)	(0.395)
$OCDS_{i,t-1}$	−0.074*	−0.073*	0.019	0.024
	(−1.832)	(−1.806)	(0.464)	(0.586)
$OIDS_{i,t-1}$	−0.517***	−0.529***	−0.051	−0.054
	(−3.522)	(−3.611)	(−0.374)	(−0.402)
R-sq	0.027	0.033	0.004	0.022
	Exporters		Importers	
	Model 1	Model 2	Model 1	Model 2
α	0.446***	0.402***	0.262***	0.253***
	(5.438)	(4.906)	(3.197)	(3.088)
$Momentum_{i,t-1}$		0.096***		0.033*
		(5.75)		(1.671)
$OSS_{i,t-1}$	−0.142**	−0.140**	−0.123*	−0.120*
	(−2.04)	(−2.016)	(−1.941)	(−1.888)
$EAS_{i,t-1}$	0.012	0.012	−0.071	−0.075
	(0.115)	(0.112)	(−0.618)	(−0.652)
$OCDS_{i,t-1}$	−0.008	−0.003	0.051**	0.052**
	(−0.336)	(−0.136)	(2.085)	(2.117)
$OIDS_{i,t-1}$	−0.197**	−0.183**	0.049	0.049
	(−2.333)	(−2.176)	(0.588)	(0.598)
R-sq	0.005	0.015	0.011	0.012

Note: This table presents the estimates for Eq. 8 (Model 1) and Eq. 9 (Model 2) for the momentum factor, estimated cross-sectionally across country groups listed in Table A1 in the Appendix. OSS: oil supply shock; EAS: economic activity shock; OCDS: oil-specific consumption demand shock; OIDS: oil inventory demand shock. *t* statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.2. Analysis of cross-sectional relationships between oil price shocks and factor premia

Tables 2 through 4 present the findings for Eq. 8 (Model 1) and Eq. 9 (Model 2) for the size, value and momentum factors respectively, computed cross-sectionally across country groups listed in Table A1 in the Appendix. We note varied effects of oil price shocks in Table 2 among the distinct country groups. While economic activity shocks are found to positively predict excess returns on the size factor in developed stock markets, we find that oil supply and inventory demand shocks serve as the most dominant predictors of excess returns associated with size in emerging stock markets. Kang et al. (2017) and Su et al. (2018) suggest that an increase in oil supply shock reflects negative information about the economic prospects, leading to heightened uncertainty. Hence, the favorable predictive impact of supply shocks on the size premium in emerging markets may represent the risk compensation that investors seek for small companies during periods of increased uncertainty. Likewise, the positive effect of inventory demand shocks could be an indication of market worries regarding future supply disruptions and uncertainty, thus predicting higher risk premia associated with firm size. At the same time, the positive effect of economic activity shocks on size in developed markets could reflect investors' search for growth opportunities in small cap firms, thus bidding up their valuations as a result of rising risk appetite associated with positive economic activity shocks.

While we do not observe any consistently significant patterns for frontier stock markets and BRICS in Table 2, we observe an interesting contrast for major commodity importers and exporters. We find that precautionary demand shocks (i.e. oil inventory demand shocks) have asymmetric predictive effects on the size premia for these two country groups with higher inventory demand shocks predicting lower (higher) excess returns on size for exporters (importers). Gong and Lin (2017) argue that oil producers generally benefit from good oil market uncertainty (positive innovations), whereas bad uncertainty is favorable to oil consumers. Accordingly, one can argue that positive innovations in oil prices due to precautionary demand shocks serve as a source of bad uncertainty, thus positively (negatively) predicting the size premia in importers (exporters). Indeed, previous works have argued that oil-specific demand shocks generally indicate uncertainty over supply of oil in the future (Kilian, 2009), while Filis et al. (2011) and Basher et al. (2012) show that upward price fluctuations in oil as a result of unanticipated demand factors decrease stock returns. Accordingly, the negative predictive effect of demand shocks on the size premium in major exporters could be a manifestation of investors' demand for value firms in these stock markets to hedge themselves against future uncertainty in the oil market. In contrast, the positive effect of precautionary demand shocks in the case of importers could be explained by the evidence in Dagher and Hasanov (2023) of lower stress in financial markets during periods when oil price rises due to demand factors, thus driving the returns on small cap stocks in importing nations as investors would be more likely to take a bet on the growth opportunities offered by these stocks.

Our observations on the size premium are partially confirmed in Table 3 when we extend the analysis to excess returns associated with the value factor. The asset pricing literature presents ample evidence that value stocks offer investors excess returns relative to growth stocks and theoretical models generally attribute the risk premium on value to the flexibility of a firm to adjust its capacity to market dynamics. In our case, we observe in Table 3 that economic activity shocks positively predict the value premium in developed markets, while oil consumption demand shocks positively predict value in both the developed and emerging stock markets. Kang and Ratti (2013a), (2015) and Kang et al. (2017) document a positive response of uncertainty to demand shocks specific to the oil market, attributing these responses to heightened uncertainty about future oil supplies. Similarly, Kilian and Murphy (2012) and Baumeister and Peersman (2013) propose that a positive shock in oil-specific demand results in increased oil prices, heightened oil production, and reduced macroeconomic activity. This evidence is further supported in other works including Basher et al. (2012) and Filis et al. (2011) who observe that positive shocks in oil prices, stemming from unexpected factors in oil demand, lead to a decline in stock returns. Top of FormLinking this evidence with the finding by Maghyereh and Abdoh (2020) that firms whose operations are more exposed to upside energy price uncertainty tend to reduce their capital investments as a result of rising operational costs, one can argue that the positive predictive relationship we observe on the value premium captures the risk premium investors require on value stocks as these firms with larger amounts of inflexible assets compared to growth firms face higher adjustment costs to unexpected changes in energy uncertainty. This finding is also consistent with Chiah et al. (2022) who link heightened energy price uncertainty to the value premium as value firms struggle more than growth firms to adjust in their operations during such periods.

In line with the findings for size in Table 2, we do not observe any significant patterns for frontier stock markets and BRICS although a positive predictive relationship between economic activity shocks and value is found for major importers, consistent with our findings with developed stock markets. In contrast, we observe for exporting economies that the sign of directional predictability running from economic activity shocks and oil demand shocks to the value premium turns negative. Considering the argument by Gong and Lin (2017) that oil producers generally benefit from good oil market uncertainty, the negative effect on value in exporting economies could be explained by investors' appetite for growth firms in these stock markets as a response of positive signals due to good oil market uncertainty captured by positive innovations in oil prices associated with precautionary demand and economic activity shocks. Nevertheless, the comparison of our findings for exporting and importing nations highlights the contrast in the response of these stock markets to disaggregated oil market shocks.

Finally, we present in Table 4 the estimates for the momentum factor across the selected country groups. We generally observe that oil shocks have a more widespread effect on momentum compared to the size and value factors, consistent with the evidence in Kumar et al. (2020), with significant results found for all country groups except for BRICS. All types of oil shocks except for consumption demand shocks are found to possess significant predictive power over momentum returns in developed and emerging stock markets. Interestingly, however, while oil shocks negatively predict momentum in developed stock markets, the opposite is the case for emerging stock markets. The negative predictive relationship between oil market shocks and momentum in developed markets is indeed consistent with the negative effect of aggregate market volatility (Wang, Xu 2015) and oil return volatility on momentum returns (Chen et al., 2017), which can be explained by time varying investor sentiment. In that regard, Wang, Xu (2015) argue that investors refrain from holding stocks with poor past performance, especially if those stocks have high information uncertainty or low credit ratings, during volatile down markets and over-sell loser stocks, resulting in low momentum payoffs as a result of the subsequent loser reversal. Given that shocks in oil prices can significantly contribute to macroeconomic uncertainty (Hailemariam et al., 2019), the negative effect of oil shocks on momentum returns could be due to the effect of these shocks on investor sentiment (Sheng et al., 2020), which in turn drives investors' risk preferences away from loser stocks in response to economic shocks.

In contrast, the positive effect that we observe on momentum in emerging stock markets is in line with the finding by Sagi and Seasholes (2007) that momentum payoffs are higher among firms with valuable growth options. The authors argue that investors become overly optimistic following positive market shocks and aggressively search for cheap stocks, thus positively contributing to momentum. In that regard, one possible explanation for the positive effect on momentum in emerging stock markets could be investors' risk-taking behavior towards growth stocks in emerging markets following positive shocks. This argument is partially supported by the finding in Table 4 that economic activity shocks possess the highest predictive effect on momentum returns (2.345 and 2.369 for Models 1 and 2 respectively) across the different oil shocks, suggesting that positive shocks associated with economic activity contributes the most to subsequent momentum returns. In the case of the other country groups, the most consistent pattern we observe is the negative effect of oil shocks on momentum in frontier, importing and exporting stock markets, in line with the evidence of a negative relationship between volatility and momentum (Wang, Xu 2015; Chen et al., 2017) with the exception of a positive effect of consumption demand shocks on momentum in importing economies that can be attributed to risk taking behavior towards growth stocks as financial market experience less stress in response to demand driven oil shocks (Dagher and Hasanov, 2023). Overall, our findings show that oil market shocks possess significant information regarding the size and direction of risk premia in global stock markets although our findings indicate heterogeneity in the response of risk premia to these shocks, depending on the market classification and the type of oil shock.

4.3. Economic implications

Clearly, the predictive relationship between oil market shocks and factor returns has important implications for asset pricing as the predictive information captured by these shocks could be a source of systematic mispricing in financial markets, which can provide new insight into the time variation in stock market anomalies. However, these findings become more meaningful if these results yield significant economic implications as well. Accordingly, to close the loop in our analysis, we examine the economic implications of our results by considering a naive investor who is currently passively invested in the aggregate stock market index. We then execute a dynamic, conditional investment strategy where the investor augments the passive index portfolio with a position in a given factor (size, value, and momentum) conditional on the size and direction of oil market shocks. Specifically, following Cepni et al. (2022), we take a position in each factor one at a time following periods of high oil market shocks characterized by the oil shock values above the 90 % quantile of each shock series, and the investor stays passive during normal times. As explained in Section 3.2.3, we compute the optimal portfolio positions in the factors by implementing the mean-variance approximations to expected utility analysis of Markowitz (2014).

Table 5 reports the performance results for the conditional investment strategy in which conditioning is based on large oil market shocks. The Sharpe ratio (SR) is the excess portfolio return divided by its standard deviation and hedging effectiveness (HE) measures the reduction in portfolio risk as per Ederington (1979). We observe in the table that augmenting the passive index portfolio within a factor-based strategy conditional on oil market shocks can significantly improve the risk-return tradeoff for the investor. Specifically, our analysis shows that augmenting the passive index with a value-based factor portfolio in developed markets in response to oil supply and economic activity shocks improves the Sharpe ratio to 0.0773 and 0.0777, respectively, compared to 0.068 for the passive index. These two strategies are also found to reduce portfolio risk by 7.08 % and 6.54 % respectively, when the strategy is conditioned on oil supply and economic activity shocks. While tilting the passive portfolio towards value is also found to improve the risk-return profile of investors for emerging markets and BRICS, we see that a momentum-based strategy offers the greatest reduction in portfolio risk in most country groups, ranging from 6.9 % for emerging stock markets to 7.42 % for commodity importers. These findings are further confirmed visually in Fig. 4 which illustrates the cumulative returns for an initial investment of $1 in the optimal factor-based investment strategy conditional on large oil price shocks against the passive index portfolio represented as the dashed line. We see that augmenting the passive market index portfolio within a factor-based strategy, conditioned on oil market shocks significantly amplifies the portfolio returns.

Next, motivated by the evidence in the literature of asymmetries in the effect of energy price uncertainty on corporate investment, output growth and financing costs (Demirer et al., 2015; Gong and Lin, 2017; Rahman and Serletis, 2011; Maghyereh and Abdoh, 2020; Prodromou and Demirer, 2020), we replicate our economic analysis by differentiating between positive and negative oil market shocks. To that end, we consider an investment strategy where the passive investor takes a position in the size, value, and momentum factors following periods of large positive (negative) oil shocks, characterized by the oil shock values above (below) the 90 % quantile of each shock series. Tables 6 and 7 report the performance results for the proposed active investment strategy conditional on large positive and negative oil market shocks, respectively. We observe markedly distinct patterns comparing the two tables. First, we observe that the investment strategy conditioned on oil market shocks yields much higher Sharpe ratios when the conditioning is applied to positive oil shocks. Likewise, we find that the reduction in portfolio risk is much greater for positive oil shocks in Table 6 than the case for negative oil shocks in Table 7. While this finding is consistent with the generally positive predictive relationship between oil price shocks and factor returns reported in Tables 2–4, it also suggests that the sign of the oil market shock should be considered in active factor strategies.

Comparing the findings across the different country groups and oil shocks, we observe in Table 6 that momentum yields the greatest

Table 5
Economic Analysis.

	Supply Shocks			Economic Activity Shocks			Consumption Demand Shocks			Inventory Demand Shocks		
	Size	Value	Mom	Size	Value	Mom	Size	Value	Mom	Size	Value	Mom
	Developed Markets											
Mean	0.3068	0.3176	0.2256	0.2817	0.3211	0.2385	0.2688	0.2605	0.2752	0.2431	0.2839	0.2069
Std. Dev.	4.1045	4.1089	4.1804	4.2309	4.1338	4.1585	4.2187	4.2813	4.2176	4.2883	4.2113	4.1802
SR	0.0747	0.0773	0.0540	0.0666	0.0777	0.0573	0.0637	0.0609	0.0653	0.0567	0.0674	0.0495
HE	−0.0718	−0.0708	−0.0546	−0.0432	−0.0652	−0.0596	−0.0459	−0.0318	−0.0462	−0.0302	−0.0476	−0.0547
	Emerging Markets											
Mean	0.2561	0.2794	0.2474	0.2684	0.2595	0.2292	0.1923	0.2291	0.1929	01638	0.2390	0.1634
Std. Dev.	4.1948	4.0948	4.0667	4.1298	4.0721	4.1714	4.0832	4.1457	4.1689	4.1976	4.1082	4.1499
SR	0.0610	0.0660	0.0608	0.0621	0.0637	0.0549	0.0471	0.0552	0.0462	0.0390	0.0585	0.0393
HE	−0.0396	−0.0625	−0.0690	−0.0624	−0.0654	−0.0426	−0.0628	−0.0485	−0.0431	−0.0365	−0.0629	−0.0475
	Frontier Markets											
Mean	0.4929	0.5122	0.5117	0.3272	0.2862	0.3293	0.1642	0.2394	0.2469	0.2703	0.3470	0.3805
Std. Dev.	4.2070	4.2564	4.1934	4.3854	4.4800	4.4708	4.5724	4.5548	4.5551	4.5303	4.5811	4.5683
SR	0.1171	0.1203	0.1220	0.0746	0.0639	0.0736	0.0359	0.0525	0.0542	0.0596	0.0757	0.0833
HE	−0.1011	−0.0906	−0.1041	−0.0630	−0.0428	−0.0448	−0.0231	−0.0268	−0.0268	−0.0321	−0.0212	−0.0240
	BRICS											
Mean	0.2857	0.3623	0.3093	0.2360	0.2862	0.2240	0.2483	0.3185	0.2177	0.2561	0.2574	0.2970
Std. Dev.	4.1854	4.1656	4.1402	4.2789	4.2862	4.2483	4.2556	4.2536	4.2530	4.1806	4.2112	4.1786
SR	0.0682	0.0869	0.0747	0.0551	0.0667	0.0527	0.0583	0.0748	0.0519	0.0612	0.0611	0.0710
HE	−0.0562	−0.0607	−0.0664	−0.0351	−0.0335	−0.0420	−0.0403	−0.0408	−0.0409	−0.0573	−0.0504	−0.0577
	Exporters											
Mean	0.2920	0.3520	0.4014	0.2437	0.3264	0.2856	0.2290	0.2542	0.2809	0.2136	0.2761	0.2491
Std. Dev.	4.1105	4.1354	4.0938	4.1474	4.1593	4.2087	4.2330	4.2873	4.2068	4.1598	4.1797	4.2033
SR	0.0710	0.0851	0.0980	0.0588	0.0785	0.0679	0.0541	0.0593	0.0668	0.0514	0.0661	0.0593
HE	−0.0704	−0.0648	−0.0742	−0.0621	−0.0594	−0.0482	−0.0427	−0.0304	−0.0487	−0.0593	−0.0548	−0.0494
	Importers											
Mean	0.3430	0.2934	0.2840	0.2898	0.2757	0.2342	0.2344	0.3078	0.2386	0.2290	0.2605	0.2548
Std. Dev.	4.1579	4.1112	4.2120	4.1648	4.2031	4.1760	4.2510	4.2267	4.2508	4.2362	4.1765	4.1987
SR	0.0825	0.0714	0.0674	0.0696	0.0656	0.0561	0.0551	0.0728	0.0561	0.0541	0.0624	0.0607
HE	−0.0597	−0.0703	−0.0475	−0.0581	−0.0495	−0.0556	−0.0387	−0.0441	−0.0387	−0.0420	−0.0555	−0.0505

Note: This table reports the performance metrics for the dynamic investment strategy that involves the passive market index and size, value, and momentum factors conditional on oil market shocks. SR: Sharpe Ratio and HE: Hedging Effectiveness computed following Ederington (1979) as $HE = 1 - \frac{Var(y_p)}{Var(y_{unhedged})}$.

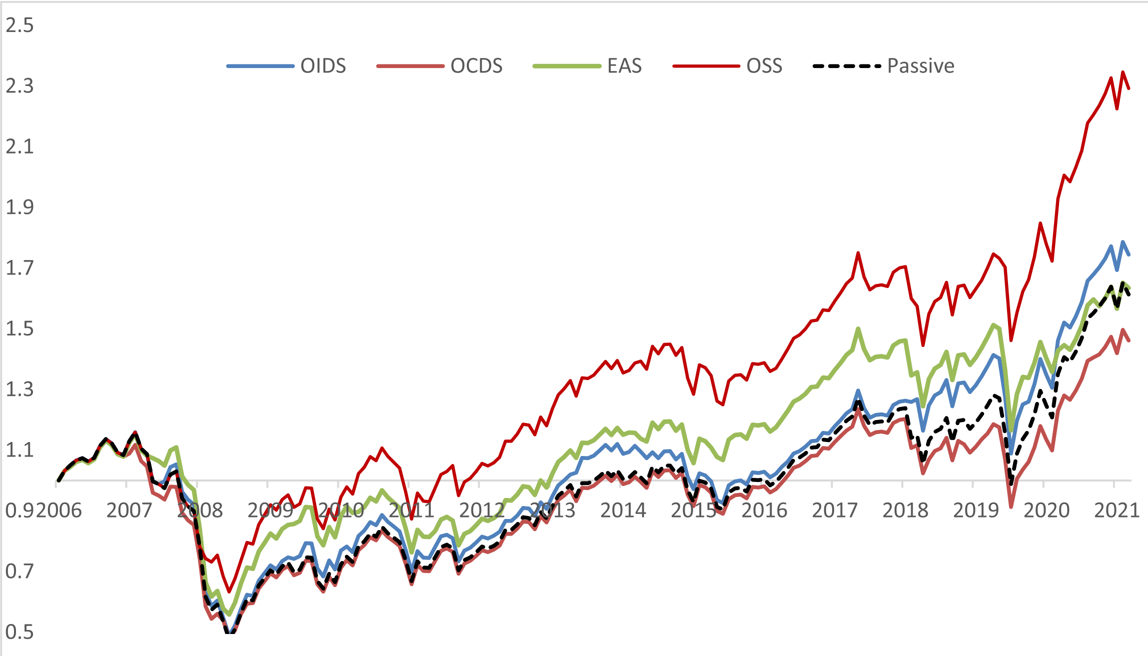

Fig. 4. Cumulative returns for dynamic investment strategies conditioned on large oil market shocks. **Note:** This figure depicts the cumulative returns for an initial investment of $1 in the optimal factor-based investment strategy conditional on large oil price shocks against the passive index portfolio represented as the dashed line. OSS: oil supply shock; EAS: economic activity shock; OCDS: oil-specific consumption demand shock; OIDS: oil inventory demand shock.

improvement in the Sharpe ratios and especially conditional on positive supply shocks, while tilting the portfolio towards size following large positive supply shocks achieves the greatest reduction in portfolio risk which can be as high as 20.4 % for the size-based portfolio that involves emerging market stocks. At the same time, the Sharpe ratio obtained from the conditional strategy is found to be as high as 0.1598 when the portfolio is tilted towards momentum following large positive supply shocks, more than doubling the Sharpe ratio of 0.068 for the passive investor. This is a significant improvement in the risk-adjusted performance of the portfolio. In contrast, the findings for negative oil price shocks reported in Table 7 highlight inventory demand shocks as the optimal conditioning strategy to implement a factor-based investment approach. Interestingly, comparing the hedge effectiveness values in Tables 6 and 7, we see that conditioning the portfolio on negative oil price shocks generally offers higher reduction in portfolio risk than the case for positive oil price shocks. We find that the reduction in portfolio risk when the strategy is conditioned on large negative inventory demand shocks can be as high as 25.69 % in the case frontier stock markets with a corresponding Sharpe ratio of 0.2117 that is even higher than the highest Sharpe ratio of 0.1598 reported in Table 6. Overall, our analysis shows that the predictive relationship between disaggregated oil price shocks and factor returns can indeed be exploited in a forward-looking investment strategy by augmenting the passive index portfolios with factor-based portfolios conditional on the size and direction of oil price shocks.

The comparison of portfolio statistics reported in Tables 6 and 7 becomes visually clear when we trace the cumulative returns for an initial investment of $1 in the optimal factor-based investment strategy conditional on large positive and negative oil price shocks, depicted in Figs. 5 and 6, respectively. Comparing the two plots, we see that the dynamic strategy works the best as a potential diversification strategy in response to negative oil market shocks. While, the factor-based strategy conditional on consumption demand shocks yields the best cumulative performance when the conditioning is done on large positive oil shocks, we see in Fig. 6 that all factor-based strategies regardless of the conditioning mechanism outperform the passive strategy at all times. Furthermore, we find in both figures that the portfolio performances have witnessed a marked surge following the COVID-19 pandemic.Top of Form This is quite a striking result, suggesting that smart beta strategies can indeed be effectively improved by designing a conditional factor strategy with respect to the size and direction of oil price shocks. In sum, the economic analysis shows that the predictive links between oil market shocks and factor returns can be used to improve the profitability of smart beta strategies, an important insight for this growing segment of the managed fund industry.

4.4. Discussion

The empirical findings of this study offer valuable insights into the time-varying characteristics of economic shocks, proxied by oil market shocks, and systematic risk premia in global equity markets. Building on the well-established evidence of a significant effect of oil price shocks on equity markets, our findings extend previous works to asset pricing factors that have been the basis for factor investing strategies well utilized in the asset management industry. Although the standard linear Granger causality tests, presented in

Table 6
Economic Analysis – *positive* oil price shocks.

	(+) Supply Shocks			(+) Economic Activity Shocks			(+) Consumption Demand Shocks			(+) Inventory Demand Shocks		
	Size	Value	Mom	Size	Value	Mom	Size	Value	Mom	Size	Value	Mom
	Developed Markets											
Mean	0.2719	0.2730	0.3535	0.2933	0.3146	0.3146	0.2144	0.2392	0.2422	0.2088	0.2004	0.1429
Std. Dev.	3.5181	3.5242	3.6045	3.6268	3.6286	3.5977	3.7816	3.8825	3.7635	3.9097	3.8267	3.7585
SR	0.0773	0.0775	0.0981	0.0809	0.0867	0.0874	0.0567	0.0616	0.0644	0.0534	0.0524	0.0380
HE	−0.2044	−0.1592	−0.1849	−0.1798	−0.1794	−0.1864	−0.1448	−0.1220	−0.1489	−0.1158	−0.1346	−0.1500
	Emerging Markets											
Mean	0.2907	0.3212	0.2796	0.2373	0.2250	0.1925	0.1660	0.1771	0.1838	0.1851	0.1509	0.1631
Std. Dev.	3.3366	3.3963	3.4377	3.5238	3.7509	3.6573	3.9419	3.8178	3.9634	3.8271	3.9218	3.8768
SR	0.0871	0.0946	0.0813	0.0673	0.0600	0.0526	0.0421	0.0464	0.0464	0.0484	0.0385	0.0421
HE	−0.2040	−0.1897	−0.1798	−0.1593	−0.1413	−0.1628	−0.0976	−0.1260	−0.0927	−0.1239	−0.1022	−0.1125
	Frontier Markets											
Mean	0.4273	0.5072	0.6018	0.1606	0.1302	0.2658	0.2503	0.3473	0.2185	0.3130	0.2600	0.2630
Std. Dev.	3.8298	3.4902	3.7659	3.8934	2.4667	3.8545	3.7342	4.1106	4.0863	4.0939	4.0756	4.1698
SR	0.1116	0.1453	0.1598	0.0412	0.0528	0.0690	0.0670	0.0845	0.0535	0.0765	0.0638	0.0631
HE	−0.1818	−0.2543	−0.1954	−0.1682	−0.1932	−0.1765	−0.2022	−0.1218	−0.1270	−0.1254	−0.1293	−0.1091
	BRICS											
Mean	0.3610	0.3716	0.4443	0.3423	0.2836	0.2477	0.2367	0.3023	0.2656	0.2033	0.3355	0.2025
Std. Dev.	3.5785	3.7020	3.5989	3.7765	3.8243	3.9020	3.9379	3.8541	3.9452	3.9080	3.9763	3.9134
SR	0.1009	0.1004	0.1235	0.0906	0.0742	0.0635	0.0601	0.0784	0.0673	0.0520	0.0844	0.0518
HE	−0.1931	−0.1653	−0.1885	−0.1485	−0.1377	−0.1201	−0.1121	−0.1310	−0.1104	−0.1188	−0.1034	−0.1176
	Exporters											
Mean	0.3404	0.4077	0.2981	0.2677	0.3039	0.2418	0.1256	0.2444	0.1636	0.1597	0.2855	0.2154
Std. Dev.	3.4426	3.5735	3.7693	3.6042	3.6675	3.7285	3.8053	3.8819	3.8452	3.8158	3.8948	3.8734
SR	0.0989	0.1141	0.0791	0.0743	0.0829	0.0649	0.0330	0.0630	0.0426	0.0419	0.0733	0.0556
HE	−0.2215	−0.1919	−0.1476	−0.1849	−0.1706	−0.1568	−0.1394	−0.1221	−0.1304	−0.1371	−0.1192	−0.1240
	Importers											
Mean	0.4233	0.3876	0.3187	0.2679	0.2487	0.2173	0.1965	0.1605	0.2370	0.2363	0.1598	0.1391
Std. Dev.	3.4923	3.6209	3.4940	3.5839	3.7110	3.7570	3.8025	3.8547	3.7610	3.7912	3.7952	3.6960
SR	0.1212	0.1070	0.0912	0.0748	0.0670	0.0578	0.0517	0.0416	0.0630	0.0623	0.0421	0.0376
HE	−0.2102	−0.1811	−0.2098	−0.1895	−0.1608	−0.1504	−0.1401	−0.1283	−0.1495	−0.1426	−0.1417	−0.1642

Note: This table reports the performance metrics for the dynamic investment strategy that involves the passive market index and size, value, and momentum factors conditional on positive oil market shocks. SR: Sharpe Ratio and HE: Hedging Effectiveness computed following Ederington (1979) as $HE = 1 - \frac{Var(y_p)}{Var(y_{unhedged})}$.

Table 7
Economic Analysis − *negative* oil price shocks.

	(-) Supply Shocks			(-) Economic Activity Shocks			(-) Consumption Demand Shocks			(-) Inventory Demand Shocks		
	Size	Value	Mom	Size	Value	Mom	Size	Value	Mom	Size	Value	Mom
	Developed Markets											
Mean	0.1753	0.2291	0.3545	0.2391	0.2421	0.3049	0.2187	0.3004	0.4210	0.2705	0.3079	0.4926
Std. Dev.	3.7826	3.5352	3.6048	3.6545	3.6082	3.7120	3.5974	3.4956	3.5707	3.5165	3.5566	3.5067
SR	0.0463	0.0648	0.0983	0.0654	0.0671	0.0821	0.0608	0.0859	0.1179	0.0769	0.0866	0.1405
HE	−0.1446	−0.1566	−0.1848	−0.1735	−0.1840	−0.1606	−0.1865	−0.2095	−0.1925	−0.2047	−0.1957	−0.2070
	Emerging Markets											
Mean	0.1027	0.1470	0.0748	0.2055	0.1881	0.1694	0.1630	0.2865	0.3115	0.2871	0.2874	0.2568
Std. Dev.	3.9133	3.7356	3.7325	3.7789	3.6523	3.8726	3.7409	3.5377	3.5780	3.4366	3.4727	3.4743
SR	0.0263	0.0376	0.0200	0.0544	0.0515	0.0437	0.0436	0.0810	0.0871	0.0835	0.0828	0.0739
HE	−0.1042	−0.1449	−0.1455	−0.1349	−0.1639	−0.1135	−0.1436	−0.1901	−0.1809	−0.2133	−0.2050	−0.2047
	Frontier Markets											
Mean	0.0386	0.0558	0.0958	0.2941	0.2298	0.4650	0.4799	0.4637	0.5778	0.2472	0.4533	0.7363
Std. Dev.	3.9898	3.9636	3.9778	3.9628	4.1163	4.0173	3.7781	3.7056	3.6100	3.7010	3.6489	3.4782
SR	0.0097	0.0141	0.0241	0.0742	0.0558	0.1157	0.1270	0.1251	0.1600	0.0668	0.1242	0.2117
HE	−0.1476	−0.1532	−0.1502	−0.1534	−0.1206	−0.1417	−0.1928	−0.2083	−0.2287	−0.2093	−0.2204	−0.2569
	BRICS											
Mean	0.2765	0.2296	0.2322	0.2118	0.4085	0.3964	0.2978	0.4423	0.3041	0.3544	0.4296	0.3722
Std. Dev.	3.7455	3.7456	3.8185	3.7802	3.7579	3.7917	3.5823	3.7704	3.6446	3.6293	3.5037	3.5430
SR	0.0738	0.0613	0.0608	0.0560	0.1087	0.1046	0.0831	0.1173	0.0834	0.0976	0.1226	0.1051
HE	−0.1554	−0.1554	−0.1390	−0.1476	−0.1526	−0.1450	−0.1922	−0.1498	−0.1782	−0.1816	−0.2100	−0.2011
	Exporters											
Mean	0.2419	0.2763	0.3032	0.2002	0.2683	0.3440	0.3467	0.2787	0.3814	0.2958	0.3841	0.4683
Std. Dev.	3.7094	3.7701	3.7482	3.6877	3.7658	3.7773	3.3909	3.5831	3.6900	3.5141	3.5928	3.4658
SR	0.0652	0.0733	0.0809	0.0543	0.0712	0.0911	0.1022	0.0778	0.1033	0.0842	0.1069	0.1351
HE	−0.1611	−0.1474	−0.1524	−0.1660	−0.1484	−0.1458	−0.2332	−0.1897	−0.1655	−0.2053	−0.1875	−0.2162
	Importers											
Mean	0.2104	0.1247	0.2281	0.3157	0.1621	0.2534	0.3073	0.3389	0.2722	0.3521	0.3709	0.4674
Std. Dev.	3.7571	3.6901	3.8640	3.6376	3.8479	3.7222	3.6856	3.6755	3.6853	3.5463	3.4015	3.4521
SR	0.0560	0.0338	0.0590	0.0868	0.0421	0.0681	0.0834	0.0922	0.0739	0.0993	0.1090	0.1354
HE	−0.1503	−0.1655	−0.1262	−0.1774	−0.1298	−0.1582	−0.1665	−0.1688	−0.1666	−0.1980	−0.2308	−0.2193

Note: This table reports the performance metrics for the dynamic investment strategy that involves the passive market index and size, value, and momentum factors conditional on negative oil market shocks. SR: Sharpe Ratio and HE: Hedging Effectiveness computed following Ederington (1979) as $HE = 1 - \frac{Var\left(y_p\right)}{Var\left(y_{unhedged}\right)}$.

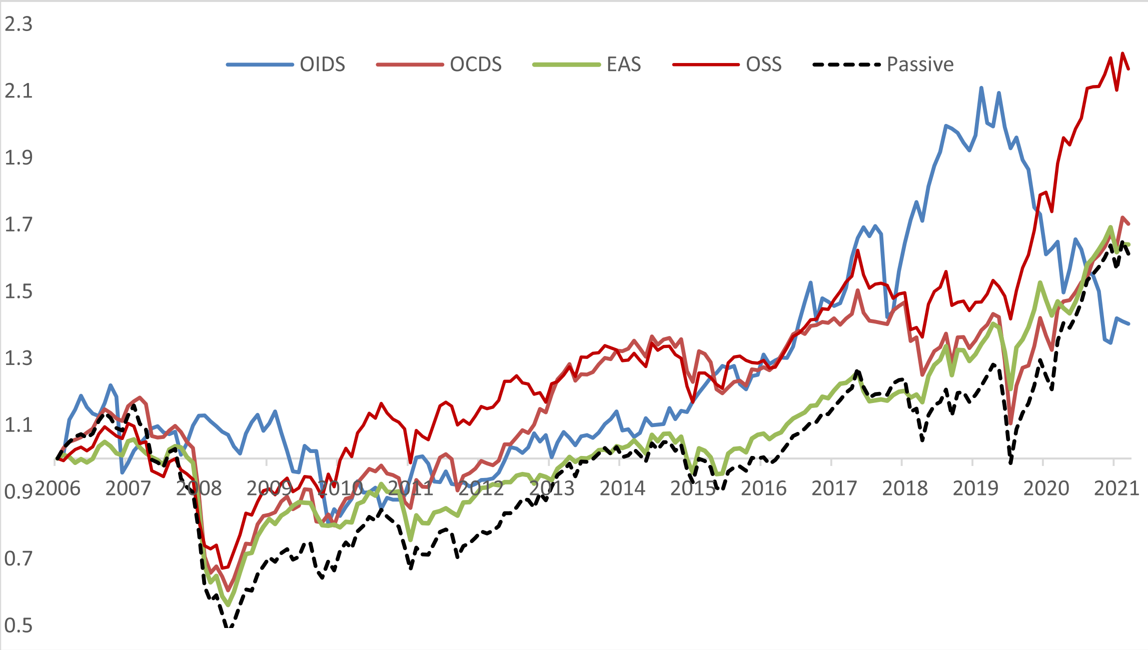

Fig. 5. Cumulative returns for dynamic investment strategies conditioned on large *positive* oil market shocks. **Note:** This figure depicts the cumulative returns for an initial investment of $1 in the optimal factor-based investment strategy conditional on large *positive* oil price shocks against the passive index portfolio represented as the dashed line. OSS: oil supply shock; EAS: economic activity shock; OCDS: oil-specific consumption demand shock; OIDS: oil inventory demand shock.

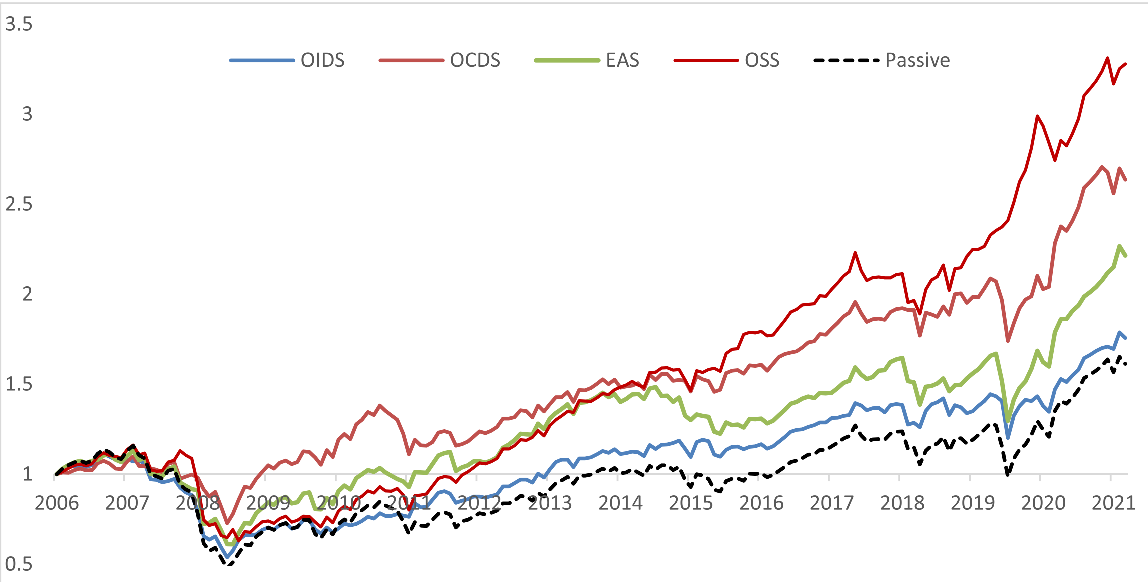

Fig. 6. Cumulative returns for dynamic investment strategies conditioned on large *negative* oil market shocks. **Note:** This figure depicts the cumulative returns for an initial investment of $1 in the optimal factor-based investment strategy conditional on large *negative* oil price shocks against the passive index portfolio represented as the dashed line. OSS: oil supply shock; EAS: economic activity shock; OCDS: oil-specific consumption demand shock; OIDS: oil inventory demand shock.

Table A2 in the Appendix, yield largely insignificant effects with several exceptions, our results from the dynamic time-varying causality tests show that disentangled oil price shocks indeed possess significant predictive power, particularly over risk premia associated with momentum, in both developed and emerging markets, especially after the global financial crisis. The predictive power of oil price shocks on momentum in particular can be explained by the close link between market stress/volatility and momentum returns (e.g. Chen et al., 2017; Dagher and Hasanov, 2023) as oil price shocks are often associated with increased market uncertainty (Sheng et al., 2020). This highlights the potentially market destabilizing effects of these shocks which in turn drives reversals in the performance of past winner and loser stocks. Furthermore, given the arguments in Berk et al. (1999) and Johnson (2002) that link momentum to the growth options of firms, one can argue that the causal effects observed in our results are a manifestation of changes in investors' growth expectations captured by these shocks. Finally, our findings show that the effect of oil market shocks on momentum returns are asymmetric depending on the market classification, indicated by a positive (negative) predictive effect for emerging and developed markets. While this finding suggests that risk premia associated with momentum can be driven by heterogeneous market shocks, it implies the possibility of momentum investing strategies across the different market segments.

In the case of the size and value premia, our analysis further points to the heterogeneity in the effect of oil price shocks on factor returns, depending on the type of shock and market classification. For example, oil supply and inventory demand shocks are found to be highly correlated with size premia in emerging markets, suggesting that small firms could be especially vulnerable to these shocks in these markets. Considering the evidence in Kang et al. (2017) and Su et al. (2018), that an increase in oil supply shock reflects negative information about the economic prospects, our findings highlight the sensitivity of small firms to economic uncertainty, particularly in emerging economies. At the same time, consumption demand shocks are found to amplify the value premia in both developed and emerging markets. Considering the argument by Chiah et al. (2022) that value firms struggle more than growth firms to adjust in their operations during periods of high energy market uncertainty, one can argue that investors require a greater premium on value firms during such periods, thus leading to a risk premium on their stock valuations. Nevertheless, our findings suggest that a portfolio of large, value firms could be used as a hedge against these shocks in active diversification strategies.

Overall, our observation that oil inventory demand shocks significantly influence size and value premia in emerging markets is consistent with Dagher and Hasanov (2023), who highlight the impact of oil-specific supply shocks on financial market stress. The significant effects of oil supply shocks on momentum returns in developed and emerging markets align with Wang, Xu (2015), who link momentum strategies to market volatility. Additionally, our results on value premia are supported by Kilian and Murphy (2012) and Chiah et al. (2022), who document the influence of oil demand shocks on investor behavior and asset pricing. This comparative analysis underscores the validity of our findings and situates them within the broader context of oil market research. Finally, our economic analysis, summarized in Tables 5 to 7 and Figs. 4 to 6, demonstrates the potential for strategic asset allocation conditional on the size and nature of oil market shocks. Specifically, our findings show that factor-based strategies that respond to significant positive or negative oil shocks can enhance portfolio efficiency, reduce risk, and achieve significantly higher risk-adjusted returns. This underscores the importance of economic implications of analyzing the forecasting dependencies between oil fluctuations and factor returns, facilitating informed decision-making regarding portfolios and asset prices.

5. Conclusion

Stock market anomalies establish the basis for factor investing strategies that have been increasingly popular in the investment management industry over the past decade. These strategies identify common characteristics of companies such as value and size which deliver identifiable and repetitive patterns of return and exploit these predictability patterns to improve portfolio returns and enhance diversification. An increasing number of studies, however, show that the trends and cycles for these factors display a great deal of time variation and the investment-based theories in the asset pricing literature argue that these factors primarily respond to economic shocks that affect investment behavior and risk perception. Interestingly, many of the drivers of the time variation in factor returns proposed in the asset pricing literature have already been documented to be closely linked to energy market uncertainty in the vast oil-stock market literature although the literature has not yet established a direct link between oil market shocks and the time variation in factor returns. Against this background, this paper takes a novel investment-focused perspective to the oil-stock market nexus by exploring the predictability of factor premia from a large set of global stock markets by disaggregated oil market shocks that capture oil market fluctuations associated with supply, demand and economic activity related factors.

Our findings establish a clear predictive relationship between disaggregated oil price shocks and factor returns in global stock markets. While our analysis highlights oil supply and precautionary demand shocks as the dominant predictors of factor returns, we document relatively stronger predictability results for the excess returns associated with value and momentum. Not surprisingly, oil shocks are found to have quite heterogenous effects on factor returns depending on the structure of the shock and stock market classification and our findings indicate markedly different predictive patterns for developed versus emerging stock markets as well as for commodity importers versus exporters, indicated by asymmetries in the response of factor returns to oil price shocks in these country groups. Further analysis shows that the predictive relationship between oil market shocks and factor returns has significant economic implications as well. Proposing a forward-looking global factor investing strategy wherein the investment positions switch between the passive and active factor positions conditioned on the size and direction of the oil market shock, we document significant improvements in the risk and return profile of investment portfolios over the passive investment strategy and that the profitability of the investment strategy depends on the sign of the oil shock.

Our findings are informative in explaining the time variation in systematic risk premia in stock markets and offer new insight into the implementation of smart beta strategies within a conditional framework in response to economic shocks. Regarding the policy implications, the finding that global oil supply and inventory demand shocks predict the size and value premia in equities highlights the need for tailored risk management approaches, particularly in emerging stock markets. While this finding highlights the vulnerability of small firms with large investments in inflexible assets to oil market shocks, it is also important in informing corporate decision makers and fund managers in these regions towards the implementation of appropriate measures against oil market shocks. Similarly, the impact of oil price shocks on momentum returns, particularly in developed markets, suggests that stabilizing oil prices could mitigate negative effects on momentum strategies and reduce market volatility. Furthermore, policymakers can find our findings informative to address the role of oil market shocks in exacerbating heterogeneity in the responses oil importers and exporters by developing targeted economic and support policies. For example, importers might implement hedging strategies to mitigate the impact of rising oil prices, while exporters could capitalize on price fluctuations to enhance economic performance. In conclusion, aligning responses to oil market shocks with financial sector policies and investment strategies can create a safety net that enhances economic stability.

For future research, it will be intriguing to expand our analysis into an out-of-sample forecasting context wherein the predictive power of disaggregated oil price shocks is evaluated in various forecasting model settings including machine learning models. A more comprehensive comparative analysis of the out-of-sample forecasting power of each type of oil shock over factor returns in a dynamic setting can also offer new insight into the time variation in systematic risk premia that has been relatively understudied. Nevertheless, our findings provide a novel starting point to further evaluate the role of oil market shocks on the evolution of stock market anomalies and stock market inefficiencies.

CRediT authorship contribution statement

Riza Demirer: Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Onur Polat:** Writing – original draft, Validation, Software, Resources, Methodology, Investigation, Formal analysis. **Amin Sokhanvar:** Writing – original draft, Validation, Software, Resources, Methodology, Investigation, Formal analysis.

Data availability

Data will be made available on request.

Appendix

Table A1
Country groups used in cross-sectional analysis.

Developed		Emerging		Frontier	
Australia	AUS	UAE	ARE	Bangladesh	BGD
Austria	AUT	Argentina	ARG	Bahrain	BHR
Belgium	BEL	Brazil	BRA	Croatia	HRV
Canada	CAN	Chile	CHL	Jordan	JOR
Switzerland	CHE	China	CHN	Kenya	KEN
Germany	DEU	Czech Rep.	CZE	Sri Lanka	LKA
Denmark	DNK	Egypt	EGY	Morocco	MAR
Spain	ESP	Greece	GRC	Nigeria	NGA
Finland	FIN	Indonesia	IDN	Oman	OMN
France	FRA	India	IND	Pakistan	PAK
UK	GBR	Kuwait	KWT	Romania	ROU
Hong Kong	HKG	South Korea	KOR	Slovenia	SVN
Iceland	ISL	Mexico	MEX	Vietnam	VNM
Ireland	IRL	Malaysia	MYS		
Israel	ISR	Peru	PER		
Italy	ITA	Philippines	PHL		
Japan	JPN	Poland	POL		
Luxembourg	LUX	Qatar	QAT		
Netherlands	NLD	Russia	RUS		
Norway	NOR	Saudi Arabia	SAU		
New Zealand	NZL	Thailand	THA		
Portugal	PRT	Turkey	TUR		
Singapore	SGP	Taiwan	TWN		
Sweden	SWE	South Africa	ZAF		
US	USA				
BRICS		Commodity Exporters		Commodity Importers	
Brazil	BRA	Australia	AUS	China	CHN
Russia	RUS	Bahrain	BHR	India	IND
India	IND	Brazil	BRA	South Korea	KOR
China	CHN	Chile	CHL	Japan	JPN
South Africa	ZAF	Canada	CAN	Germany	DEU
		Kuwait	KWT	US	USA
		Nigeria	NGA		
		Norway	NOR		

(*continued on next page*)

Table A1 (*continued*)

Developed	Emerging		Frontier
	Oman	OMN	
	Qatar	QAT	
	Russia	RUS	
	Saudi Arabia	SAU	
	UAE	ARE	

Note: The Country classifications follow the MSCI stock market classifications from https://www.msci.com/our-solutions/indexes/market-classification.

Table A2
Standard linear causality test results.

	OSS	EAS	OCDS	OIDS
	Panel A: Size			
Developed	0.200	0.111	0.245	0.994
Emerging	0.184	0.463	0.211	0.039**
Frontier	0.725	0.836	0.283	0.329
BRICS	0.693	0.645	0.275	0.366
Exporters	0.217	0.756	0.427	0.209
Importers	0.076*	0.660	0.635	0.242
	Panel B: Value			
Developed	0.033**	0.422	0.377	0.968
Emerging	0.234	0.881	0.514	0.027**
Frontier	0.734	0.297	0.994	0.699
BRICS	0.748	0.427	0.705	0.898
Exporters	0.154	0.768	0.525	0.751
Importers	0.124	0.075*	0.776	0.174
	Panel C: Momentum			
Developed	0.023**	0.710	0.557	0.280
Emerging	0.044**	0.911	0.020**	0.141
Frontier	0.129	0.770	0.883	0.003***
BRICS	0.569	0.928	0.668	0.766
Exporters	0.031**	0.537	0.672	0.746
Importers	0.146	0.460	0.117	0.790

Note. The table reports the p-values for the standard linear Granger causality tests running from each oil shock series to factor returns associated with the size (Panel A), value (Panel B), and momentum (Panel C) factors. OSS: oil supply shock; OCDS: oil-specific consumption demand shock; OIDS: oil precautionary (inventory) demand shock; EAS: economic activity shock.

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