Cross-Asset Time-Series Momentum:

Crude Oil Volatility and Global Stock Markets

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Abstract

We examine the profitability of a cross-asset time-series momentum strategy (XTSMOM) constructed using past changes in crude oil implied volatility (OVX) and stock market returns as joint predictors. We show that past changes in OVX negatively predict but past stock market returns positively predict future stock market returns globally. The XTSMOM outperforms the single-asset time-series momentum (TSMOM) and buy & hold strategies with higher mean returns, lower standard deviations, and higher Sharpe ratios. The XTSMOM can also forecast economic cycles. We contribute to the literature on cross-asset momentum spillovers as well as on the impacts of crude oil uncertainty on stock markets.

Keywords: Cross-asset predictability; Crude oil market; International stock markets; OVX; Time-series momentum

JEL classifications: G12; G15

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1. Introduction

In their seminal work, Jegadeesh and Titman (1993) show that, in US stock markets, past winners (losers) continue to be winners (losers) over the next six months to a year. Similar patterns have been documented in various asset classes, including international stocks (Rouwenhorst, 1998), bonds (Jostova et al., 2013), commodities (Miffre and Rallis, 2007), and currencies (Menkhoff et al., 2012). Moskowitz et al. (2012) introduce the time-series momentum (TSMOM), in which the strategy is determined only by an asset's past returns—that is, prior one- to twelve-month returns positively predict future returns for different asset classes (see also Goyal and Jegadeesh, 2018; Kim et al., 2016). In a recent study, Pitkäjärvi et al. (PSV; 2020) propose a cross-asset time-series momentum (XTSMOM) strategy using past bond and stock returns as predictors and find that the XTSMOM outperforms a single-asset TSMOM strategy. Past bond returns are positive predictors of stock returns, whereas past stock returns are negative predictors of bond returns.

In this paper, we incorporate the option-implied oil price volatility in XTSMOM to predict stock markets around the world. Many empirical studies have shown the negative effects of oil price uncertainty on economic growth and stock returns. Pindyck (1991) shows that if an investment's cash flow is dependent on the oil price, companies (particularly oil companies) postpone irreversible investment decisions in response to increasing oil price uncertainty. Elder and Serletis (2010) highlight that oil price uncertainty depresses current investment. They report that oil price volatility has a negative effect on investment, consumption, and aggregate output in the US. Jo (2014) finds similar results for global real economic activity. Kellogg (2014) finds that oil and gas firms reduce their investment (proxied using their oil drilling activity) when oil implied volatility increases. In addition, Kocaaslan (2019) reports that oil price uncertainty significantly increases the US unemployment rate while Nonejad (2020) shows that crude oil price volatility improves the short term forecast of US real GDP growth rate.

The predictability of oil price uncertainty (measured by oil implied volatility) stock markets can be explained by the funding constraints of financial intermediaries. Christoffersen and Pan (2018) explain that being active in multiple markets, financial intermediaries finance their trades using their own capital and/or collateralized borrowing from other intermediaries. When oil-implied volatility is high, oil derivatives market margins increase and these intermediaries become more capital constrained, leading to lower investment activity. Therefore, an increase in oil implied volatility indicates a tightening in funding constraints, which consequently affects the stock market. Consistent with this argument, Christoffersen and Pan (2018, p.5) report that “after the financialization of commodity futures markets in 2004-2005 oil volatility has become a strong predictor of returns and volatility of overall stock market.” This reasoning is also consistent with Brunnermeier and Pedersen (2009) who show that market uncertainty and funding liquidity are interrelated state variables of the stock market.

It is important to note that crude oil price uncertainty is influenced by many factors including the overall uncertainty in the financial market. For instance, Cheng et al. (2015) use changes in the Chicago Board Options Exchange Volatility Index (VIX) to proxy for shocks to financial traders' risk appetite and funding constraints. They show that financial traders reduce their futures positions when they experience lower risk absorption capabilities due to a larger exposure to the VIX. They further report a strong positive correlation between hedge fund positions and oil (and other commodities) futures returns whereas commercial hedgers have a negative correlation, consistent with the results of Büyükşahin and Robe (2014).[1] If oil price is influenced by the overall uncertainty in the financial market (proxied by the VIX), then oil price uncertainty and the VIX should be closely related. The VIX could even be a key driver of oil price uncertainty. Robe and Wallen (2016) find that the VIX captures much of what drives uncertainty in the crude oil price, proxied by oil implied volatility. The power of the VIX reflects the significant relation between equity and crude oil prices.[2]

Given all this evidence, we examine whether crude oil price uncertainty (measured by the crude oil volatility index) can be employed as a trading signal for a profitable trading strategy. We construct an XTSMOM strategy by examining the predictability of changes in the CBOE Crude Oil Volatility Index (OVX) for various stock markets around the world.[3] Using

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[1] Cheng et al. (2015, p. 1733) call this convective risk flow: "Financial traders reduced their net long positions during the crisis in response to market distress, whereas hedgers facilitated this by reducing their net short positions as prices fell." Büyükşahin and Robe (2014) find that hedge fund positions in commodity futures help predict commodity-equity cross-market linkages. See also Büyükşahin and Robe (2010).

[2] Robe and Wallen (2016) also show that macroeconomic variables contain little information regarding oil implied volatility after controlling for the VIX, consistent with these results of Kilian and Vega (2011) who find that oil price does not respond significantly to any US macroeconomic news within the day.

[3] We employ the changes in OVX to identify positive vs. negative change in oil uncertainty because the OVX

OVX data over the sample period from May 2007 to August 2021, we first show that a cross-asset momentum strategy using one-month lagged stock returns and OVX changes shows superior predictability to a single-asset momentum strategy that relies on only one-month lagged stock returns. More specifically, past stock returns can serve as positive predictors, and past OVX changes can work as negative predictors for future stock returns. The results are similar for oil-importing and oil-exporting countries. Therefore, investors cannot hedge the effect of oil implied volatility shocks across the stock markets of oil importers and exporters.

We next evaluate the stock returns and Sharpe ratios under various TSMOM and XTSMOM regimes. We find that the XTSMOM strategy with positive (negative) past stock returns and negative (positive) past OVX changes generates the largest positive (negative) future stock market returns and Sharpe ratios. We also compare the economic performance of the XTSMOM with the TSMOM and buy & hold strategies. We document that the XTSMOM has superior performance, with higher mean returns and higher Sharpe ratios than the two alternatives. Furthermore, we find that the alpha of XTSMOM returns remains positive and highly significant after controlling for Carhart's (1997) four factors, the VIX, and its components (Bekaert et al., 2013; Bekaert and Hoerova, 2014), the Amihud (2002) illiquidity measure, the MSCI World index, the USD index, and value and momentum premiums across several asset classes (Asness et al., 2013). These results are robust after accounting for

index is highly serially correlated. Furthermore, the OVX index is non-stationary whereas its first difference is stationary. The use of first difference will remove the systematic pattern in the autocorrelation. This approach is consistent with studies such as Ang et al. (2006), Bloom (2009) and Christoffersen and Pan (2018) who use also the first difference in volatility as uncertainty shocks.

transaction costs and various adjustments to the stock return and crude oil volatility signals.

To provide supportive evidence of our economic story, we examine whether the lagged changes in OVX can forecast funding liquidity proxies of financial intermediaries. We find that funding constraints increase following an increase in oil uncertainty. This leads to lower investment activities and stock market returns. Hence, the predictive power of the changes in oil uncertainty on stock market returns can be explained by the funding liquidity argument of Christoffersen and Pan (2018).

Finally, we explore the possible link between momentum strategies, such as the TSMOM and the XTSMOM, and the real economy by focusing on key economic indicators such as the industrial production index, the unemployment rate, and the inflation rate. We find that the XTSMOM can predict economic cycles. In particular, the long (short) XTSMOM portfolio—namely, positive (negative) stock returns and negative (positive) OVX changes—can point to good (bad) economic times, with higher (lower) industrial production, decreasing (increasing) unemployment rates, and lower (higher) inflation.

It is important to note that the response of stock returns to oil price shocks can be positive or negative, depending on the source of the oil price shock. We follow Kilian (2009) to decompose oil price shocks into supply, aggregate demand, and oil-specific demand shocks. We observe that supply and oil-specific demand shocks decrease XTSMOM returns, but aggregate demand shock does not. Our findings indicate that the XTSMOM performance is only partially explained by the various oil shocks.

Our study extends the literature on the global impacts of oil uncertainty (e.g., Guo and Kliesen, 2005; Kwon, 2020; Gao et al., 2022). We find that OVX changes can serve as a significant predictor of stock markets. We complement the results of Christoffersen and Pan (2018), who highlight the importance of funding constraints, by incorporating XTSMOM into the predictability of oil implied volatility for global stock returns.

We organize the remainder of the paper as follows. We discuss the data in Section 2. Section 3 explains the methodology and reports the empirical results. We conduct further analyses in Section 4. Section 5 concludes.

2. Data and Descriptive Statistics

2.1. Data Sources

We download crude oil, stock market, and economic data at a monthly frequency from various sources. As a measure of crude oil volatility, we use the Crude Oil Exchange Traded Fund (ETF) Volatility Index (OVX) obtained from Refinitiv Datastream. The OVX is an estimate of the expected 30-day volatility of crude oil as priced by the United States Oil Fund (USO). The Chicago Board of Exchange (CBOE) first published the OVX on May 9, 2007. Thus, we start our sample period in May 2007 and end in August 2021.

For the stock market data, we obtain the monthly MSCI total return index for various countries from Refinitiv Datastream.[4] To remove the effect of exchange rate differences, we

[4] The Morgan Stanley Capital International (MSCI) stock index is often tracked by exchange traded funds (ETFs)

download all equity indices in USD. Third, we collect the US short-term (one-month) interest rates from Kenneth French's website. For this study, we consider a US investor who takes a position in international stock markets to exploit the XTSMOM strategy and invests in the US risk-free rate when not taking positions. In total, we consider 59 countries, including 44 oil-importing and 15 oil-exporting countries. Our final sample consists of 8,220 country-month observations.[5]

For each country, we download from Refinitiv Datastream the MSCI small- and large-cap indices to construct the SMB (small minus big) risk factor (calculated as the MSCI small- minus the MSCI large-cap returns). We also download the MSCI value and growth indices to construct the HML (high minus low) risk factor (calculated as the MSCI value minus the MSCI growth returns). To proxy for stock market risk, we use the VIX obtained from Refinitiv Datastream. Bekaert, Hoerova, and Lo Duca (2013) explain that the VIX has two components: conditional variance (which captures uncertainty) and the variance premium (which captures risk aversion). We obtain data on the VIX components from Marie Hoerova's website.

In our study, we also examine whether the impact of oil price shocks on stock markets differs depending on whether the change in the price of oil is driven by demand or supply shocks. As such, we extract the crude oil shocks from the following datasets: (1) Kilian's Global

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and futures contracts in different countries (Angelidis and Tessaromatis, 2017). Hence, using the MSCI stock market index is realistic to ensure that the XTSMOM strategy is implementable.

[5] The list of these countries and their stock index symbols is in Appendix A.

Economic Activity as an indicator of the aggregate oil demand,[6] (2) the change in world crude oil production, including lease condensate, as an indicator of the change in global crude oil supply,[7] (3) the US crude oil composite acquisition cost by refiners[8] deflated by US CPI[9] as an indicator of the real crude oil price. We collect monthly data and extract the crude oil shocks from January 1974 to August 2021 and match them with our sample period for our regression analysis.

Finally, we collect information on several economic fundamentals. Like PSV (2020), we focus on industrial production, the unemployment rate, and the inflation rate, as they are consistently available across the countries in our sample. These macroeconomic data are collected at a monthly frequency from Refinitiv Datastream.

2.2. Descriptive Statistics

Table 1 reports the statistics of the OVX changes and the pooled stock excess returns for all the countries and for oil-importing and oil-exporting countries. Panel A reports that the changes in OVX is only slightly positive over the sample period, with an average of 0.05% per month (*t*-statistic of 0.07) and a standard deviation of 12.18% per month.[10] The OVX changes are also

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[6] https://www.dallasfed.org/research/igrea/.

[7] https://www.eia.gov/international/data/world/.

[8] https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=R0000_3&f=M/.

[9] https://www.bls.gov/cpi/.

[10] Our sample has more months with negative than positive OVX changes. Specifically, 54.4% of our sample

positively skewed and have large tails (i.e., high kurtosis). With respect to the pooled stock returns, we observe positive monthly mean excess returns at around 0.417% per month for all countries, 0.392% per month for oil-importing countries, and 0.494% per month for oil-exporting countries. On average, the pooled stock returns are negatively skewed and have large tails. The last column suggests that the OVX changes and equity excess returns are not persistent, with first autocorrelation (AR(1)) coefficients ranging from -0.057 (for the OVX changes) and 0.093 (for oil-exporting countries excess returns).

[Insert Table 1 here]

3. Empirical Results

In this section, we first investigate whether the signs of past OVX changes can predict future stock returns in an international context. We then show that these signals can be exploited in an XTSMOM strategy. Next, we provide the economic rationale for the predictive power of past OVX changes predictability and study how the XTSMOM returns relate to oil supply/demand shocks. Finally, we report the robustness of our results.

3.1. Single- and Cross-Asset Time-Series Predictability

Before we apply the cross-asset time-series predictability model, we start by explaining the

period has decreases in the OVX, 44.4% increases in the OVX, and another 1.2% has no changes. In an unreported result, we observe some clusters of positive OVX change signals that coincide with financial crises, such as the global financial crisis (2008), the 2014 Russian financial crisis (second half of 2014), and the COVID-19 pandemic (early 2020).

single-asset time-series predictability model. In particular, we can assess whether the signs of past stock market returns are predictive of future returns using the following pooled panel regression:

$$r_t^{e,i} = \alpha + \beta^e sign\left(r_{t-1}^{e,i}\right) + \varepsilon_t^i, \tag{1}$$

where $r_t^{e,i}$ is the stock market excess returns of country *i* in month *t*, $sign\left(r_{t-1}^{e,i}\right)$ is the sign of the previous month market *i* excess returns, $\{\alpha, \beta^e\}$ are the parameters to estimate, and ε_t^i are the residuals. This single-asset model has been used in various studies, such as Moskowitz et al. (2012), Kim et al. (2016), and Goyal and Jegadeesh (2018). In our study, we focus on a lookback period of one month. However, we also use the average past stock excess return over the previous year instead of a one-month lag for robustness. We now extend our analysis of time-series predictability by examining whether the signs of lagged OVX changes (ΔOVX_{t-1}) are predictive of future stock market returns. To do so, we pool all stock market returns and regress them on the sign of lagged OVX changes as well as the sign of its own lagged excess returns as follows:

$$r_t^{e,i} = \alpha + \beta^e sign\left(r_{t-1}^{e,i}\right) + \beta^{OVX} sign(\Delta OVX_{t-1}) + \varepsilon_t^i. \tag{2}$$

The coefficients $\{\alpha, \beta^e, \beta^{OVX}\}$ are estimated using a pooled panel regression.[11] In Table 2, we

[11] Before estimating Equation (2), we examine the associations between the equity and crude oil markets. More specifically, we applied a panel Granger-causality test using the Dumitrescu-Hurlin approach on the equity return and OVX change series. This approach runs standard Granger-causality regressions for each country individually.

report the results of Equation (2) along with the White-corrected t-statistics clustered by year-month. For comparison, we also report the results of Equation (1) with the sign of the one-month lagged stock market returns as a predictor. We present the results for all countries (Panel A), oil-importing countries (Panel B), and oil-exporting countries (Panel C).

[Insert Table 2 here]

Panel A shows that the predictability of the sign of the lagged OVX changes is negative and significant at the 1% level for all countries (t-statistic of –3.59). This result suggests that stock returns are 1.00% per month lower when the one-month lagged OVX change is positive, i.e., when the crude oil volatility increased in the previous month. Adding the one-month lagged OVX change increases the adjusted R^2 by 1.46% compared to the single-asset model with its own one-month lagged stock returns.[12] To ensure that these results hold across different periods in our sample, we re-estimated Equation (2) using two equal-sized subsamples, June 2007 – July 2014 and August 2014 – August 2021. In both cases, the negative predictability of $sign(\Delta OVX)$ persists. These results are available from the authors.

It then takes the average of the test statistics, standardized to follow a standard normal distribution. We find that, regardless of the number of lags employed (from one to five), OVX changes Granger cause equity returns, but not the reverse. It therefore supports our motivation for the cross-asset time-series momentum effect between crude oil volatility and stock markets.

[12] In unreported results, we employed alternative lags for the stock excess return and OVX changes in Equations (1) and (2), i.e., $sign\left(r_{t-h}^{e,i}\right)$ and $sign(\Delta OVX_{t-h})$ with h=1, …, 12, respectively. The results show positive predictability from past stock excess returns up to the fifth lag, with a reversal afterward; however, none of the lags are statistically significant. Otherwise, the sign of the first lag of OVX change is the only statistically significant lag. This result can be explained by how the OVX index is obtained. Specifically, the OVX represents the market expectations about future oil volatility at the one-month horizon, therefore, its predictability is stronger at a one-month horizon. These results are available upon request from the authors.

Robe and Wallen (2016) document that the VIX is one of the main drivers of the market expectations of crude oil implied volatility. Therefore, the OVX is closely linked to the VIX. To examine whether the OVX changes drive stock market returns beyond the VIX or its components, we include the sign in VIX changes ($sign(\Delta VIX)$) and the sign in the changes in its two components ($sign(\Delta VIX_CV)$and $sign(\Delta VIX\_VP)$). In addition, we control for stock market predictors, such as size (SMB) and book-to-market (HML) risk factors. We observe that part of the predictive ability of XTSMOM is explained by the control variables. However, the sign of the one-month lagged OVX change remains negative and statistically significant, suggesting that the crude oil volatility index provides a trading signal beyond that of stock market information.

[Insert Table 2 here]

Panels B and C of Table 2 further show that the lagged OVX changes predictability is negative and significant for oil-importing and oil-exporting countries, with *t*-statistics of similar magnitude for the coefficients and adjusted R^2. In all three panels, we observe that $sign(\Delta VIX)$ and the signs of the two components of VIX are insignificant at the 10% level, but $sign(\Delta VIX\_VP)$ is marginally significant at the 10% level in Panels A and C.

Although positive oil price changes have negative impacts on oil-importing economies and positive impacts on oil-exporting countries (Barsky and Kilian, 2004; Wang et al., 2013), the effect of changes in oil implied volatility is of similar magnitude and sign in both groups. This finding is consistent with Diaz et al. (2016) who find a negative response by the G7 stock markets (including Canada, an oil-exporting country) to an increase in world oil price volatility. Our finding is also consistent with Wang (2021) who document the propagation of oil price shocks through banks' operations including a decline in demand deposit, a surge in credit line drawdowns and a jump in troubled loans, particularly for banks with significant operations in oil-concentrated countries. We therefore conclude that oil implied volatility generally has a negative impact on all our sample countries.

Appendixes B and C report the results of Equation (2) by country. The negative relationship between the sign of the one-month lagged OVX changes and the country's stock return is persistent across countries. Among our 59 countries, 58 have a negative β^{OVX} coefficient, and they are statistically significant at the 10% level or better in 30 countries (about 51% of the countries in our sample).

In our next analysis, we assess the economic value of the XTSMOM strategy. We report the average monthly excess returns and Sharpe ratios by the stock market and OVX change regimes in Table 3. We present the results for the stock returns and OVX changes momentum regimes separately in Panel A. In Panel B, we use both stock returns and OVX changes as joint predictors.

[Insert Table 3 here]

Panel A shows that stock returns are highest (lowest) during positive (negative) stock momentum regimes. Stock returns are also the highest (lowest) during negative (positive) OVX changes. These findings confirm the regression results in Table 2 and are consistent with past stock returns being positive predictors of future stock returns and past OVX changes being negative predictors of future stock returns. In Panel B, we show that a profitable trading strategy is formed from combining the lagged stock returns and OVX changes as joint predictors. The highest stock excess returns and Sharpe ratios are observed in months with positive past stock excess returns combined with negative past OVX changes. In contrast, the lowest stock excess returns and the lowest Sharpe ratios are observed in months with negative past stock returns combined with positive past OVX changes.

3.2. Cross-Asset Time-Series Strategy

Previously, we showed that past OVX changes are a significant predictor of future stock market returns in an international context, and this predictability is not subsumed by the information of the lagged stock market return and various control variables. In this section, we exploit this pattern in a cross-asset trading strategy. First, we explain how to construct the single-asset TSMOM strategy. Then we describe how we modify it to construct the XTSMOM strategy.

The single-asset TSMOM strategy takes a long (short) position in the stock market index of country *i* in month *t* if its past-month excess return is positive (negative). The position is held for one month, after which the previous steps are repeated. Specifically, the single-asset TSMOM strategy excess return, $r_t^{TSMOM,i}$, is calculated as follows:

$$r_t^{TSMOM,i} = sign(r_{t-1}^{e,i}) \cdot r_t^{e,i} . \tag{3}$$

We form a diversified TSMOM portfolio with this single-asset TSMOM return series by taking an equal-weighted average of the individual assets' TSMOM returns—that is, $TSMOM_t = \frac{\sum_{i=1}^{N} r_t^{TSMOM,i}}{N}$, where i denotes the country, and N is the total number of countries in the sample.[13]

The XTSMOM strategies are constructed by incorporating the cross-asset predictor as well as the single-asset time-series predictor. More specifically, we take a long (short) position in a given month if the past monthly stock market excess return is positive (negative) and that of the OVX change is negative (positive). Otherwise, we hold a risk-free asset—that is, the one-month US interest rate. We hold the position for one month and then repeat the previous steps. The XTSMOM excess returns, $r_t^{XTSMOM,i}$, for country i in month t are obtained as follows:

$$r_t^{XTSMOM,i} = \begin{cases} +r_t^{e,i}, if\ sign\left(r_{t-1}^{e,i}\right) > 0 \text{ and } sign(\Delta OVX_{t-1}) < 0 \\ -r_t^{e,i}, if\ sign\left(r_{t-1}^{e,i}\right) < 0 \text{ and } sign(\Delta OVX_{t-1}) > 0 \\ \quad 0, \qquad\qquad\qquad\qquad\qquad\qquad \text{otherwise.} \end{cases} \tag{4}$$

We form diversified cross-sectional TSMOM portfolios, denoted XTSMOM, by taking equal-weighted averages of the individual assets' XTSMOM returns—that is, $XTSMOM_t = \frac{\sum_{i=1}^{N} r_t^{XTSMOM,i}}{N}$, where i denotes the country, and N is the total number of countries in the sample.

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[13] Disentangling the TSMOM from risk parity investment is not trivial (see, e.g., Kim et al., 2016). We therefore follow PSV (2020) and do not apply volatility scaling in the TSMOM strategy.

Table 4 reports the performance of the XTSMOM and TSMOM strategies together with the buy & hold strategy, which we use as a benchmark.[14] We report the performance for all the countries (Panel A), for oil-importing countries (Panel B), and oil-exporting countries (Panel C). In Panel A, the buy & hold strategy obtains a positive mean excess return of 0.41% per month (5.03% per year) but is statistically insignificant. The TSMOM strategy obtains a positive mean excess return of 0.52% per month (6.42% per year), also statistically insignificant.

[Insert Table 4 here]

Notably, the XTSMOM outperforms all the strategies, with a mean excess return of 0.79% per month (9.90% per year), significant at the 5% level, and a monthly Sharpe ratio of 0.175. We test for the difference in mean returns using a *t*-test of differences in means between XTSMOM versus buy & hold (H_1: $Mean_{XTSMOM} - Mean_{B\&H} = 0$) and XTSMOM versus TSMOM (H_2: $Mean_{XTSMOM} - Mean_{TSMOM} = 0$). We reject the null hypothesis in both cases at the 5% level with *t*-statistics of 2.30 (H_1) and 2.07 (H_2), confirming that the XTSMOM mean return is economically and statistically superior to those of the two alternatives. We also test the significance of the Sharpe ratios using Opdyke's (2007) Sharpe ratio test with a null hypothesis that the Sharpe ratio is equal to zero (H_3: $SR_j = 0$ for any strategy *j*). We reject the null hypothesis at the 1% level (*p*-value of 0.004) for the XTSMOM strategy, suggesting that

[14] The buy & hold strategy invests equally in all the countries and maintains a long position in our holding period, which is one month. The same process is repeated for the subsequent periods.

not only the mean return but also the risk-adjusted performance of XTSMOM is statistically and economically significant. The XTSMOM portfolio also has lower risk, with a lower standard deviation and similar kurtosis but more positive skewness than those of the TSMOM. These results are consistent for both the oil-importing (Panel B) and oil-exporting (Panel C) countries. We also test the difference in mean returns for the XTSMOM strategy between the oil-importing and oil-exporting countries in Panels B and C, respectively (H_4: $Mean_{XTSMOM(exporting)} - Mean_{XTSMOM(importing)} = 0$). Consistent with our earlier results, we do not find any statistical difference between the mean returns, with a *t*-statistic of 1.44.[15]

Figure 1 plots the future value of $1 invested with the buy & hold, TSMOM, and XTSMOM strategies. Consistent with Table 4, the XTSMOM strategy outperforms both TSMOM and buy & hold, with final earnings of $3.61 at the end of our sample period. In comparison, the TSMOM and buy & hold strategies have final earnings of $2.26 and $1.62, respectively. We also consider alternative investment dates, i.e., $1 invested from May 2007 until June 2014 and $1 invested from June 2014 until August 2021. The plots in Appendix D show that the XTSMOM strategy yields a higher profit than the buy & hold and TSMOM strategies in both subperiods. These findings suggest that the cross-asset time-series

[15] It is probable that the US stock market better predict other stock markets, and therefore, yields a more challenging benchmark (Rapach et al., 2013). We tested this by replacing the lagged local stock returns with the lagged US stock returns as the equity signal in the XTSMOM strategy. We find that using local stock market return as signals offers a better performance (Sharpe ratio of 0.175) compared to using US stock returns (Sharpe ratio of 0.151). The results are available from the authors upon request.

momentum strategy remains profitable, regardless of the initial investment date.

[Insert Figure 1 here]

Figure 2 plots the Sharpe ratios of the XTSMOM and TSMOM strategies for each country in our sample. In general, the Sharpe ratios of the former are superior to those of the latter in all countries except Bulgaria and Chile. Hence, we conclude that the XTSMOM strategy is superior not only in the context of an international stock market portfolio but also in most countries.

[Insert Figure 2 here]

We further analyze the excess returns of the XTSMOM strategies by calculating their alphas based on the following models:

$$XTSMOM_t = \alpha + \beta_1 TSMOM_t + \beta_2 MKT_t + \beta_3 SMB_t + \beta_4 HML_t + \beta_5 UMD_t + \beta_6 \Delta VIX_t + \beta_7 \Delta ILLIQ_t + \epsilon_t, \quad (5)$$

$$XTSMOM_t = \alpha + \beta_1 TSMOM_t + \beta_2 MSCI\_World_t + \beta_3 VAL\_Everywhere_t + \beta_4 MOM\_Everywhere_t + \beta_5 \Delta usd_t + \epsilon_t, \quad (6)$$

where $XTSMOM_t$ denotes the excess return in month t of the XTSMOM portfolio, and $TSMOM_t$ denotes the excess return for the TSMOM portfolio. In Equation (5), we include the three factors of Fama and French (1993), $\{MKT_t, SMB_t, HML_t\}$, and the momentum factor of Carhart (1997), UMD_t, for developed markets collected from Kenneth French's website. We also include ΔVIX_t, which is either the VIX changes or the changes in its components, and the changes in the Amihud (2002) illiquidity ratio, $\Delta ILLIQ_t$,[16] as a measure of liquidity risk. In Equation (6), $MSCI\_World_t$ is the MSCI World returns (in USD) collected from Refinitiv Datastream.[17] $VAL\_Everywhere_t$ and $MOM\_Everywhere_t$ are the cross-sectional value and momentum returns obtained across asset classes from the AQR data library used by Asness et al. (2013). We also control for foreign exchange risk through the log changes in the USD index downloaded from Refinitiv Datastream.[18] Finally, ϵ_t denotes the residuals.

Table 5 reports the regression estimates from Equation (5). In Panel A, we show that using all the countries, the XTSMOM strategy obtains a sizable abnormal performance or alpha of 0.413% per month (4.96% per year), on average, and is statistically significant at the 5% level. The control variable TSMOM is significant at the 1% level, while other market risk factors, such as *HML*, *UMD*, ΔVIX and ΔVIX_VP, are statistically significant at the 10% level or better. These coefficients suggest that the countries in the long (short) XTSMOM portfolio tend to be growth (value), losers (winners), with high (low) uncertainty and risk aversion. Similar results are observed for the oil-importing (Panel B) and oil-exporting (Panel C)

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[16] The Amihud illiquidity ratio captures the price impact of trading. The illiquidity measure for month *t* is calculated as $ILLIQ_t = \frac{1}{D}\sum_{d=1}^{D}\frac{|r_d^{US}|}{\$Vol_d^{US}}$, where r_d^{US} is the stock return on day *d* for the daily MSCI US index, $\$Vol_d^{US}$ is the daily dollar trading volume in the US, and *D* is the total number of trading days in a month. Data are collected from Refinitiv Datastream.

[17] MSCI World Index comprises large- and mid-cap stock performance across 23 developed countries.

[18] The US dollar (USD) index is a measure of the value of the US dollar relative to the value of a basket of six world currencies—the euro, Swiss franc, Japanese yen, Canadian dollar, British pound, and Swedish krona.

countries.

[Insert Table 5 here]

The results for Equation (6) are reported in Table 6. In Panel A, we observe that the alpha from the XTSMOM strategy is positive at 0.46% per month (5.69% per year) and significant at the 1% level. This outperformance persists even after world stock returns, cross-sectional value and momentum returns, and the log changes in the USD index are taken into account.

[Insert Table 6 here]

Finally, we implement a spanning test in which we regress the monthly returns of the XTSMOM and TSMOM portfolios on each other. The results in Appendix E confirm that the XTSMOM is not equivalent to the TSMOM. For instance, Panel A shows that the XTSMOM alpha is still positive (0.36% per month, on average) and significant at the 5% level when we control for the TSMOM. It is important to note that the TSMOM is negative but insignificant when we control for the XTSMOM. In other words, the information captured by the TSMOM is included in the XTSMOM, but not the reverse.

3.3. Funding constraints of financial intermediaries

In this study, we argue that changes in oil price volatility may predict stock market returns due to the funding constraints of financial intermediaries. To provide supportive evidence of our economic story, we have regressed several funding liquidity proxies on one month lagged changes in OVX, similar to Christoffersen and Pan (2018). If changes in OVX affect funding liquidity of financial intermediaries, it should be able to forecast the funding liquidity proxies. More specifically, we estimate the following regression:

$$FLiquidity_t = \alpha + \beta_1 \Delta OVX_{t-1} + \epsilon_t, \tag{7}$$

where $FLiquidity_t$ is the measure of funding constraints of financial intermediaries in month t. We consider four funding liquidity proxies: (1) the TED spread from St. Louis Fed (obtained as the difference between the 3-month LIBOR and 3-Month Treasury bills), (2) the credit spread from St. Louis Fed (the difference between Baa and 10-year constant maturity Treasury bonds), (3) the Betting-against-Beta (BAB) factor of Frazzini and Pedersen (2014) from AQR, and (4) the International Bank index returns from Refinitiv Datastream. Increases in both the TED and credit spreads reflect funding illiquidity. If an increase in oil implied volatility decreases funding liquidity, we expect the regression coefficients for the lagged OVX changes to be positive. The BAB factor measures returns of a portfolio that is long low-beta stocks and short high-beta stocks. Low BAB factor signals funding constraints. Hence, if an increase in oil implied volatility decreases funding liquidity, we expect the regression coefficients to be negative. Finally, International Bank index is an equally weighted stock price index of large global commercial banks. Decreases in the bank index return imply that broker–dealers are more constrained and/or face higher margin requirements. Thus, if an increase in oil implied volatility decreases funding liquidity, we expect the regression coefficients to be negative.

Table 7 reports the estimates, Newey-West corrected t-statistics and adjusted-R^2. In line with Christoffersen and Pan (2018), we find that an increase in OVX changes increases future TED and credit spreads. Although the coefficients have the expected sign, they are not statistically significant. We also find that an increase in OVX changes decreases the BAB factor and International Bank index returns in the next period. Their coefficients have the expected sign and are significant at the 1% and 10% level, respectively. These results provide supportive evidence that the economic linkage between the changes in oil implied volatility and future stock markets returns can be explained by the financial intermediary channel, consistent with Christoffersen and Pan (2018).

INSERT TABLE 7 HERE

3.4. Oil Supply and Demand shocks

Kilian and Park (2009) show that the impact of oil price shocks on US stocks differs, depending on whether the change in the price of oil is driven by demand or supply shocks in the oil market. To examine whether the performance of XTSMOM is explained by such shocks, we first extract the oil shocks using the structural VAR (SVAR) model developed by Kilian (2009). More specifically, we identify oil supply, global demand, and oil-specific demand shocks using world crude oil production (as a proxy for oil supply), Kilian's global economic activity (as a proxy for global oil demand), and the deflated US crude oil composite acquisition cost by refiners (as a proxy for the real price of oil).[19] We then estimate the following regression to assess the effect of shocks to crude oil on the performance of the XTSMOM strategy,

$$XTSMOM_t = \alpha + \beta_1 Supply_t + \beta_2 Agg\_demand_t + \beta_3 Oil\_demand_t + \epsilon_t, \qquad (8)$$

[19] The structural VAR results are available upon request from the authors.

where $XTSMOM_t$ are the excess returns of the XTSMOM strategy at month t, $Supply$ is the oil supply shock, Agg_demand_t is the aggregate demand shock, Oil_demand_t is the oil-specific demand shock, and ϵ_t is the residual.

The results reported in Panel A of Table 8 show that supply and oil-specific demand shocks have negative and significant coefficients. This finding suggests that an unexpected increase in oil production (which causes a decrease in the real price of oil) or an unexpected increase in the precautionary demand for crude oil (which causes an increase in the real price of oil) decreases the XTSMOM returns. We do not find the aggregate demand shock coefficient to be statistically significant, suggesting that an unexpected change in aggregate demand does not explain the performance of the XTSMOM strategy. More importantly, the constant remains positive and statistically significant. These results are consistent across the all-country sample, as well as for oil-importing (Panel B) and oil-exporting (Panel C) countries.

The Theory of Storage (Working, 1933; Gorton et al., 2012) links levels of inventories with price volatility. High inventories are associated with a decrease in price volatility, and low inventories with an increase in price volatility. In line with this argument, we interpret the negative coefficient for oil-specific (or precautionary) demand in Table 5 as the return of XTSMOM strategy being lower during periods of low oil uncertainty, i.e., when precautionary demand for oil is high. Similarly, an increase in oil supply reduces oil uncertainty. As such, oil supply shocks lead to lower profitability for the XTSMOM strategy. To test the above claim, we split our sample into periods of high oil uncertainty (i.e., when the OVX is higher than its full sample mean) and periods of low oil uncertainty (i.e., when the OVX is lower than its full sample mean). The Sharpe ratio of the XTSMOM strategy for all countries in periods of high oil uncertainty (0.283) is superior to that in periods of low oil uncertainty (0.040). The results suggest the XTSMOM strategy performs strongly during periods of high oil uncertainty.[20]

[Insert Table 8 here]

3.5. Robustness to the XTSMOM Strategy

We perform several robustness tests of the XTSMOM strategy based on the following: (1) using the past 12-month mean stock return as the stock return signal, (2) using the difference in the level of OVX and its 12-month moving average as the oil uncertainty signal, (3) after accounting for transaction costs and short-selling constraints, (4) using the stock market excess returns in local currency, (4) using an alternative scale of the XTSMOM returns, and (5) after orthogonalizing the OVX series.

3.5.1. Average 12-Month Past Returns as the Stock Market Signal

So far, we observe that the TSMOM offers inferior performance to the XTSMOM. This might be because the past-month stock return is a poor and noisy signal for future stock returns. To circumvent this issue, the literature suggests employing the average of a larger window as the stock return signal in a TSMOM strategy (see, e.g., Moskowitz et al., 2012; PSV, 2020). In this

[20] In a further analysis, we study which type of oil shocks give rise to the oil uncertainty predictability. We regress the OVX changes on the contemporaneous oil supply and demand shocks. We find that OVX changes are contemporaneously affected by oil-specific (or precautionary) demand shocks. The importance of the oil-specific demand shocks is in line with Kilian (2009) who states, "oil price shocks historically have been driven mainly by a combination of global aggregate demand shocks and precautionary demand shocks, rather than oil supply shocks, as is commonly believed." In other words, a positive oil-specific demand shock is associated with an increase in the inventory of oil and a decrease in oil implied volatility. Therefore, we conclude that the predictability from OVX changes is partially explained by the oil-specific demand shocks.

robustness test, we use the average of the previous 12-month excess returns as the stock market signal in the XTSMOM strategy, keeping the one-month lagged OVX change as the signal of oil implied volatility.

Figure 3 shows the robustness results. The second set of bar charts shows that using the average of the previous 12-month return as the stock market signal yields a monthly Sharpe ratio of 0.145 (XTSMOM), 0.004 (TSMOM), and 0.069 (buy & hold). Although the magnitude is smaller than the baseline result, XTSMOM still outperforms the TSMOM and buy & hold strategies.

[Insert Figure 3 here]

3.5.2. Alternative Oil Uncertainty Signal

As an alternative oil uncertainty signal, we employ the difference between the level of OVX and its 12-month moving average. We use this as our oil signal in Equation (4) and evaluate the performance of the XTSMOM strategy. The third set of bars in Figure 3 plots the Sharpe ratios of XTSMOM, TSMOM and buy & hold strategies based on this alternative oil uncertainty signal. The XTSMOM strategy obtains a Sharpe ratio of 0.168 which is superior to those of TSMOM (0.121) and buy & hold (0.062) strategies. Therefore, we can conclude that the performance of XTSMOM strategies does not hinge on how we define the oil uncertainty signal.

3.5.3. Transaction Costs and Short-Selling Constraints

The profitability of the TSMOM and XTSMOM strategies might be affected by transaction costs. To address this concern, we calculate the net return of the buy & hold, TSMOM and XTSMOM strategies as follows,

$$r_{t+1}^{P} = \sum_{i=1}^{N} w_{i,t} r_{t+1}^{e,i} - \sum_{i=1}^{N} TC_i \cdot \left| w_{i,t} - w_{i,t-1^+} \right|, \tag{8}$$

where $w_{i,t}$ is the weight assigned to the ith country index based on the buy & hold, TSMOM or XTSMOM strategy at month *t*,[21] $w_{i,t^+} \equiv w_{i,t} \cdot \left(1 + r_{t+1}^{e,i}\right)$ is the actual portfolio weight right *before* the next rebalancing at $t+1$, and $r_{t+1}^{e,i}$ is the monthly return of the ith country index from month t to month $t+1$. TC_i is the transaction costs for the ith country index. We follow the transaction costs documented by Angelidis and Tessaromatis (2017), which we also report in Appendix A. These transaction costs are based on the half-trading spread of BlackRock's ETFs and Global X's ETFs, which track the MSCI stock market index for each country.[22] The results are reported in Figure 3. As expected, the performance of the XTSMOM strategy is slightly weaker after the transaction costs are accounted for, with a monthly XTSMOM Sharpe ratio of 0.126. However, it is still superior to that of the TSMOM (0.069) and buy & hold (0.027) strategies.[23]

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[21] The weights of the buy & hold are $w_{i,t} = 1/N$, those of the TSMOM are $w_{i,t} = sign\left(r_t^{TSMOM,i}\right)/N$, and those of the XTSMOM are $w_{i,t} = sign\left(r_t^{XTSMOM,i}\right)/N$.

[22] For countries for which transaction costs are not available, we take a conservative approach and use the highest half-trading spread (i.e., 0.43%) reported in Angelidis and Tessaromatis (2017).

[23] We also calculated the hypothetical breakeven transaction cost that would make our strategy unprofitable. We find that the hypothetical half spread, averaged across all the sample countries, is 0.72%. This is substantially higher than the maximum half spread of the ETFs in our sample (0.43%).

Currently, our strategies allow for short positions in international markets. In practice, short selling may be prohibited in some markets. We therefore replicate the baseline results with short-selling restrictions, i.e., we only allow long positions in our portfolios and invest in the risk-free rate when our strategies suggest going short. We obtained an even better XTSMOM performance with a Sharpe ratio of 0.201 (compared to 0.175 that is reported in Panel A of Table 4) for all the countries, and this is still superior to the TSMOM (0.163) and buy & hold (0.069) benchmarks that also do not allow short-selling. Thus, our main finding is not driven by the possibility of shorting global equity markets.

3.5.4. Stock Market Excess Returns in Local Currency

To ensure that our results are not driven by the dollar effect, we test if our results are robust to the currency used for calculating the stock market returns. Specifically, we consider a US investor who invests locally, i.e., we conduct all our analysis using equity returns in local currencies (in excess of the local risk-free rate). Stock market data and short-term interest rates are obtained from Refinitiv Datastream. Figure 3 shows that the choice of the currency does not affect the performance of the XTSMOM strategy. The monthly XTSMOM Sharpe ratio is 0.176, whereas those of the TSMOM and buy & hold strategies are 0.012 and 0.050, respectively. Therefore, our results hold regardless of whether we use excess returns in US dollars or local currency.

3.5.5. Scaled XTSMOM Returns

So far, our reported results are based on the unscaled XTSMOM excess returns. PSV (2020) scale up all the portfolio weights of the cross-asset strategy so that, for each month, the amount of capital allocated to the active positions is the same for both the XTSMOM and TSMOM strategies. Thus, we scale the XTSMOM excess returns following PSV (2020). Figure 3 further shows that the scaled XTSMOM offers a monthly Sharpe ratio of 0.170, which outperforms those of the TSMOM (0.114) and buy & hold (0.069) strategies.

3.5.6. Orthogonalized XTSMOM Strategy

Robe and Wallen (2016) find that the OVX is closely linked to the VIX. In this robustness test, we orthogonalize the OVX against the VIX. We follow the Modified Gram-Smith process, which is a method commonly used in mathematics for orthogonalizing a set of vectors. We use crude oil uncertainty signal based on the sign of the orthogonalized OVX changes (ΔOVX_orthog) in Equation (4), instead of OVX changes (ΔOVX). We then recalculate the XTSMOM returns.

The performance of XTSMOM is slightly weaker once the OVX has been orthogonalized against the VIX. For instance, the XTSMOM Sharpe ratio with the orthogonalized OVX changes is 0.138 (compared to 0.175 with just the OVX changes). This implies that part of the predictability in the OVX signal comes from the VIX. However, XTSMOM still outperforms the benchmarks, suggesting that the signal provided by OVX is also useful for predicting stock market returns. We postulate this is because OVX captures changes in the expectations of oil market participants such as the fundamentals in the oil demand and supply, as well as fears and changes in oil market participants' risk aversion. These factors are not captured by the VIX. Our results show that these oil-specific factors contain predictive information about the stock markets beyond the information contained in the VIX.

3.5.7. Subsample Analysis

When it was first introduced, the USO was structured to take positions in the front-month WTI light sweet crude oil futures. Over the years, this holding policy changed as follows: (1) in January 2009, the USO started using the front month through WTI futures and over-the-counter positions; (2) in July 2013, the USO returned to using only the front-month WTI futures contract; (3) in April 2020, USO started holding positions in various WTI futures maturities in addition to the front-month WTI futures contract.[24] These policy changes might affect our results. To assess whether these changes affect our results, we split our sample into four periods: (1) May 2007 to December 2008, (2) January 2009 to June 2013, (3) July 2013 to March 2020, and (4) April 2020 to August 2021. Then, we evaluate the performance of each trading strategy. The results of this subsample analysis are reported in Appendix F.

In general, we observe that the XTSMOM strategy outperforms TSMOM in all subperiods except the last one (April 2020 - August 2021). We note that this subperiod is the

[24] We confirmed this using the (end-of-month) USO holdings data from Morningstar.

shortest (17 months) and starts with the erratic month of April 2020, when the crude oil futures price fell below zero for the first time since its inception in March 1983. Surprisingly, during this last subperiod, buy & hold offered much higher returns than the other two strategies in all subperiods, and the returns on TSMOM and XTSMOM are nearly zero. Nevertheless, more data are needed in the future to examine the impact on the results of the policy change in April 2020.[25]

Next, we assess whether the XTSMOM performance is affected by crisis periods. We therefore consider periods of NBER (National Bureau of Economic Research) recessions and expansions. Brusa, Savor, and Wilson (2020) show that US macroeconomic policy has a larger effect on foreign country stock markets than local macroeconomic policy. As such, we use the NBER cycle to identify crises in our sample countries. The middle two columns in Appendix F show that XTSMOM offers a higher Sharpe ratio than TSMOM during expansions and, especially, recessions. As expected, the buy & hold strategy performs well during expansions and poorly during recessions. Therefore, we conclude that financial crises do not affect the outperformance of XTSMOM relative to TSMOM. Finally, we split the sample into two equal subsamples to ensure that our results hold across different periods in our sample. The first

[25] The COVID-19 pandemic might also affect OVX change signals since the first quarter of 2020: first, a large drop in demand without a decrease in production, then, a substantial decrease in production, and, finally, strong recovery in demand without a similar increase in production (Today in Energy, 2021). An alternative reason for the results of the last subperiod is that the USO invests in many contracts along the curve. Thus, it is related less to current oil price expectations and more to the average of current and future expectations. All this warrants further research.

subperiod is from June 2007 to July 2014 and the second is from August 2014 – August 2021. The last two columns in Appendix F show that in both subperiods, the Sharpe ratio of XTSMOM strategy is higher compared to the benchmarks.

4. Additional Results

4.1. The XTSMOM Smile

Moskowitz et al. (2012) demonstrate that, when plotted against stock market returns, the returns of the TSMOM strategy take the shape of a smile, suggesting that the time series momentum strategy works better under extreme market conditions. We examine whether the same is true of the XTSMOM strategy when we compare monthly excess returns of the TSMOM and XTSMOM portfolios against the monthly developed stock market excess returns from Kenneth French's website.

[Insert Figure 4 here]

In Figure 4, we observe that both the TSMOM and XTSMOM strategies take a smile shape, though they are not perfectly symmetrical. The shape of the XTSMOM smile is more pronounced in both the positive and negative return domains. These results suggest that, from a portfolio diversification perspective, the XTSMOM portfolio is valuable because of the slightly higher returns it offers during periods when the market return is negative. Similarly, the XTSMOM portfolio also offers higher returns during periods when the market return is positive.

4.2. The XTSMOM and the Economy

Finally, we explore the possible link between the XTSMOM strategy and the real economy by investigating future changes in economic variables, such as industrial production, unemployment, and inflation, under various TSMOM and XTSMOM regimes. To do so, we report the average next-12-month changes in economic indicators under momentum regimes with positive/negative stock returns, positive/negative OVX changes, and a combination of both.

Table 9 reports the average values of the macroeconomic variables in basis points under various momentum regimes. Panel A shows that positive stock returns and negative OVX changes are associated with better future economic prospects—that is, higher industrial production, a lower unemployment rate, and lower inflation. Therefore, the TSMOM seems to be related to future economic outcomes.

Panel B reports the averages of the macroeconomic variables across different XTSMOM regimes. Periods of positive stock returns and negative OVX changes are associated with the highest industrial production (IP) index changes and the lowest unemployment rate. In addition, these periods are associated with declining inflation. Therefore, the long XTSMOM portfolio predicts good economic times. Periods of negative stock returns and positive OVX changes are associated with the lowest IP changes, the largest increase in the unemployment rate, and the highest inflation rate. Therefore, the short XTSMOM portfolio predicts hard economic times.

These results are consistent with the literature showing that uncertainty in crude oil prices has a significant impact on the global economy and stock market returns (e.g., Guo and Kliesen, 2005; Jo, 2014; Kwon, 2020; Gao et al., 2022). For instance, Gao et al. (2022) find that option-implied oil volatility is a strong negative predictor of economic growth beyond the standard financial, macroeconomic, and policy uncertainty measures. Therefore, we conclude that the XTSMOM is superior to the TSMOM strategy in predicting economic cycles.

[Insert Table 9 here]

5. Conclusions

We document a cross-asset time-series momentum (XTSMOM) strategy in crude oil volatility and international stock markets. Using a sample of 59 stock markets in 44 oil-importing and 15 oil-exporting countries, we show that past stock excess returns are positive predictors and past crude oil implied volatility index (OVX) changes are negative predictors of future stock market excess returns. This XTSMOM strategy outperforms the TSMOM in terms of larger mean excess returns, lower standard deviations, and higher Sharpe ratios. The predictive power of oil price uncertainty for the stock markets can be explained by the funding constraints of financial intermediaries. In addition, we show that the XTSMOM contains information about future changes in real economic conditions. Specifically, the long (short) XTSMOM portfolio—namely, positive (negative) stock returns and negative (positive) OVX changes —

can point to good (bad) economic times, with higher (lower) industrial production, declining (increasing) unemployment rates, and less (more) inflation. The XTSMOM gives a better indication of future economic activity than a single-asset TSMOM strategy.

Our study is the closest to PSV (2020) who document an XTSMOM strategy in bond and stock markets. We contribute to the literature by constructing an XTSMOM strategy between option-implied crude oil volatility and stock returns. We also contribute to research on the impacts of oil price uncertainty on stock market returns (e.g., Christoffersen and Pan, 2018; Kwon, 2020; Gao et al., 2022).

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Appendix A. List of countries in the sample

Panel A: Oil-importing countries				*Panel B: Oil-exporting countries*			
No.	Country	Return index	TC	No.	Country	Return index	TC
1	Australia	MSAUST$	0.0215%	1	Argentina	MSARGT$	0.4312%
2	Austria	MSASTR$	0.1306%	2	Brazil	MSBRAZ$	0.0149%
3	Bangladesh	MSBNGS$	0.4312%*	3	Canada	MSCNDA$	0.0182%
4	Belgium	MSBELG$	0.0537%	4	Colombia	MSCOLM$	0.4312%
5	Bulgaria	MSBLGN$	0.4312%*	5	Denmark	MSDNMK$	0.0800%
6	Chile	MSCHIL$	0.0621%	6	Egypt	MSEGYT$	0.4312%*
7	China	MSCHIN$	0.0248%	7	Estonia	MSESTN$	0.4312%*
8	Croatia	MSCROA$	0.4312%*	8	Malaysia	MSMALF$	0.0380%
9	Czech Republic	MSCZCH$	0.4312%*	9	Mexico	MSMEXF$	0.0122%
10	Finland	MSFIND$	0.1226%	10	Norway	MSNWAY$	0.1201%
11	France	MSFRNC$	0.0195%	11	Qatar	MSQATA$	0.4312%*
12	Germany	MSGERM$	0.0168%	12	Russia	MSRUSS$	0.0681%
13	Greece	MSGREE$	0.0746%	13	Saudi Arabia	MSSAUD$	0.4312%*
14	Hong Kong	MSHGKG$	0.0227%	14	UAE	MSUAEI$	0.4312%*
15	Hungary	MSHUNG$	0.4312%*	15	Vietnam	MSVIET$	0.4312%*
16	India	MSINDI$	0.0159%				
17	Indonesia	MSINDF$	0.0421%				
18	Ireland	MSEIRE$	0.1620%				
19	Israel	MSISRL$	0.1682%				
20	Italy	MSITAL$	0.0336%				
21	Jamaica	MSJMCA$	0.4312%*				
22	Japan	MSJPAN$	0.0434%				
23	Lithuania	MSLITH$	0.4312%*				
24	Morocco	MSMORC$	0.4312%*				
25	Netherlands	MSNETH$	0.0339%				
26	New Zealand	MSNZEA$	0.1542%				
27	Pakistan	MSPAKI$	0.4312%*				
28	Peru	MSPERU$	0.1269%				
29	Philippines	MSPHLF$	0.0614%				
30	Poland	MSPLND$	0.4312%*				
31	Portugal	MSPORD$	0.1689%				
32	Romania	MSROMN$	0.4312%*				
33	Serbia	MSSERB$	0.4312%*				
34	Singapore	MSSING$	0.0388%				
35	Slovenia	MSSLVN$	0.4312%*				
36	South Africa	MSSARF$	0.0592%				
37	South Korea	MSKORE$	0.0087%				
38	Spain	MSSPAN$	0.0152%				
39	Sweden	MSSWDN$	0.0359%				
40	Taiwan	MSTAIW$	0.0315%				
41	Thailand	MSTHAF$	0.0673%				
42	Turkey	MSTURK$	0.0657%				
43	UK	MSUTDK$	0.0268%				
44	US	MSUSAM$	0.0042%				

This table reports the list of countries in the data sample and the Refinitiv Datastream ticker symbols for the stock market index for 44 oil-importing (Panel A) and 15 oil-exporting countries (Panel B). *TC* are the transaction costs from Angelidis and Tessaromatis (2017). The sample period is from May 2007 to August 2021. * indicates the highest available transaction cost.

Appendix B. Time-series analysis: oil-importing countries

Dependent variables: $r_t^{e,i}$	α		$\beta^{e,i}$		$\beta^{OVX,i}$		$Adj\ R^2$(%)
Australia	0.004	[0.74]	0.082	[1.00]	-0.012**	[–2.29]	3.14
Austria	0.000	[0.04]	0.091	[0.81]	-0.011	[-1.45]	1.55
Bangladesh	0.001	[0.26]	0.048	[0.86]	-0.010**	[-2.25]	1.09
Belgium	0.001	[0.09]	0.119	[1.00]	-0.010**	[-2.26]	3.47
Bulgaria	-0.006	[-0.84]	0.293**	[2.31]	-0.006	[-0.76]	8.67
Chile	0.001	[0.20]	-0.081	[-0.77]	-0.006	[-1.13]	-0.22
China	0.006	[0.99]	0.090	[1.06]	-0.006	[-1.26]	-0.54
Croatia	0.000	[0.05]	-0.025	[-0.22]	-0.014***	[-2.97]	3.16
Czech Republic	0.003	[0.42]	0.068	[0.92]	-0.013**	[-2.37]	2.66
Finland	0.004	[0.68]	0.050	[0.66]	-0.006	[-1.17]	0.01
France	0.004	[0.78]	-0.014	[-0.20]	-0.008	[-1.61]	0.29
Germany	0.004	[0.77]	-0.008	[-0.11]	-0.010**	[-1.98]	0.52
Greece	-0.012	[-1.24]	0.074	[0.90]	-0.005	[-0.51]	-0.33
Hong Kong	0.006	[1.17]	0.037	[0.34]	-0.007*	[-1.75]	0.53
Hungary	0.003	[0.43]	0.065	[0.70]	-0.015**	[-2.11]	2.04
India	0.007	[1.08]	0.005	[0.07]	-0.007	[-1.28]	-0.44
Indonesia	0.006	[0.83]	0.129	[1.37]	-0.007	[-1.07]	1.62
Ireland	-0.001	[-0.11]	0.089	[0.76]	-0.005	[-0.92]	0.57
Israel	0.002	[0.49]	-0.010	[-0.14]	-0.013***	[-3.14]	4.26
Italy	0.001	[0.12]	0.036	[0.51]	-0.006	[-1.09]	-0.20
Jamaica	0.011*	[1.87]	0.055	[0.69]	-0.001	[-0.15]	-1.03
Japan	0.002	[0.68]	0.004	[0.05]	-0.011***	[-2.86]	4.27
Lithuania	0.006	[1.00]	0.146	[0.94]	-0.003	[-0.38]	1.30
Morocco	0.001	[0.35]	0.024	[0.20]	-0.009**	[-1.97]	2.60
Netherlands	0.007	[1.31]	0.018	[0.19]	-0.007	[-1.60]	0.18
New Zealand	0.005	[0.96]	0.054	[0.79]	-0.012**	[-2.33]	3.09
Pakistan	-0.002	[-0.27]	0.009	[0.11]	-0.019***	[-2.75]	3.68
Peru	0.005	[0.66]	-0.058	[-0.66]	-0.009	[-1.46]	-0.12
Philippines	0.005	[0.95]	-0.002	[-0.04]	-0.006	[-1.23]	-0.44
Poland	0.001	[0.11]	0.025	[0.37]	-0.010	[-1.56]	0.17
Portugal	-0.001	[-0.25]	0.049	[0.73]	-0.005	[-1.02]	-0.15
Romania	0.005	[0.64]	0.078	[1.00]	-0.019**	[-2.31]	3.11
Serbia	-0.004	[-0.51]	0.194**	[2.10]	-0.017**	[-2.40]	5.73
Singapore	0.003	[0.62]	0.008	[0.08]	-0.012***	[-2.87]	2.03
Slovenia	0.000	[0.06]	0.085	[0.79]	-0.012**	[-2.58]	3.33
South Africa	0.004	[0.73]	-0.067	[-1.06]	-0.010*	[-1.87]	0.57
South Korea	0.006	[0.92]	-0.013	[-0.19]	-0.011**	[-2.08]	0.69
Spain	0.002	[0.29]	0.000	[0.00]	-0.007	[-1.10]	-0.41
Sweden	0.006	[1.03]	0.039	[0.43]	-0.010*	[-1.84]	1.20
Taiwan	0.008	[1.45]	0.024	[0.23]	-0.016***	[-3.52]	5.35
Thailand	0.007	[1.22]	0.061	[0.66]	-0.005	[-0.80]	-0.25
Turkey	0.001	[0.15]	0.031	[0.42]	-0.006	[-0.80]	-0.77
UK	0.002	[0.34]	0.068	[0.71]	-0.006	[-1.51]	0.96
US	0.009**	[2.06]	-0.071	[-0.85]	-0.009**	[-2.19]	1.14

This table reports the predictability of cross-asset time series using the signs of one-month lagged equity market returns and OVX changes per country—that is, $r_t^{e,i} = \alpha + \beta^{e,i} sign(r_{t-1}^{e,i}) + \beta^{OVX,i} sign(\Delta OVX_{t-1}) + \varepsilon_t^i$ for i=1, …, N, and N is the total number of countries in our sample, for the subsample of oil-importing countries. Newey-West corrected t-statistics are reported in square brackets. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. The sample period is from May 2007 to August 2021.

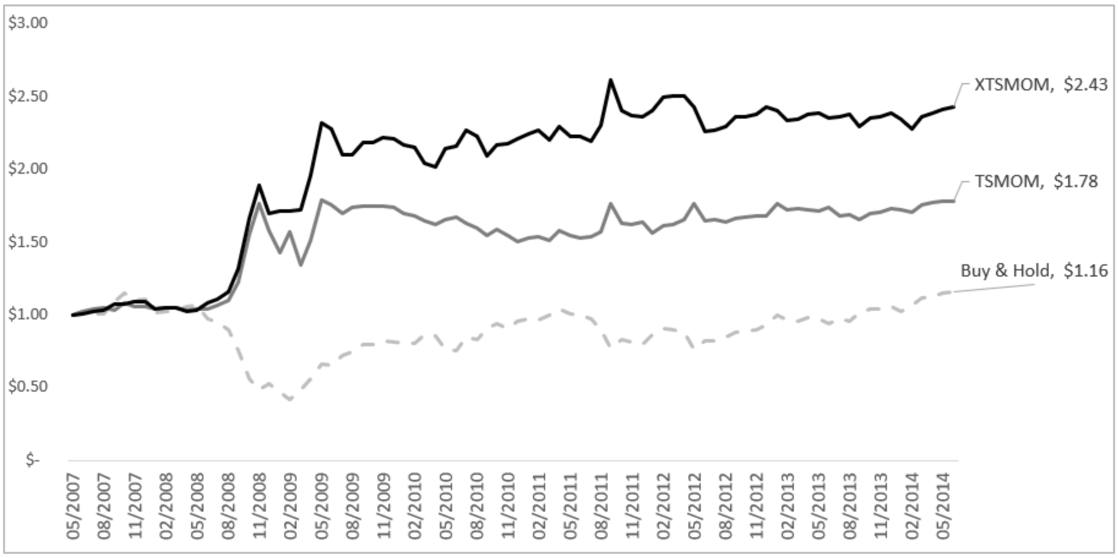
Appendix C. Time-series analysis: oil-exporting countries

Dependent variables: $r_t^{e,i}$	α		$\beta^{e,i}$		$\beta^{OVX,i}$		$Adj\ R^2(\%)$
Argentina	0.006	[0.67]	0.088	[0.92]	-0.013	[-1.21]	0.96
Brazil	0.004	[0.47]	0.080	[1.08]	-0.012	[-1.62]	1.53
Canada	0.004	[0.80]	0.003	[0.03]	-0.010**	[-2.45]	1.32
Colombia	0.004	[0.60]	-0.029	[-0.41]	-0.009	[-1.52]	-0.27
Denmark	0.007	[1.37]	0.169	[1.38]	-0.008*	[-1.87]	4.77
Egypt	0.001	[0.09]	-0.019	[-0.22]	-0.014**	[-2.02]	1.24
Estonia	0.003	[0.39]	-0.038	[-0.33]	-0.014**	[-2.04]	1.18
Malaysia	0.001	[0.35]	0.129*	[1.91]	-0.008**	[-2.36]	4.29
Mexico	0.002	[0.38]	-0.007	[-0.11]	-0.011*	[-1.68]	0.58
Norway	0.002	[0.34]	0.027	[0.22]	-0.015***	[-2.63]	2.58
Qatar	0.006	[1.02]	0.070	[0.79]	-0.006	[-1.26]	0.32
Russia	0.004	[0.44]	0.104	[0.89]	-0.015*	[-1.94]	3.39
Saudi Arabia	0.006	[0.94]	0.046	[0.45]	0.000	[0.06]	-2.29
UAE	0.003	[0.39]	0.141	[0.91]	-0.009	[-1.61]	2.90
Vietnam	0.002	[0.38]	0.142**	[2.20]	-0.003	[-0.35]	1.13

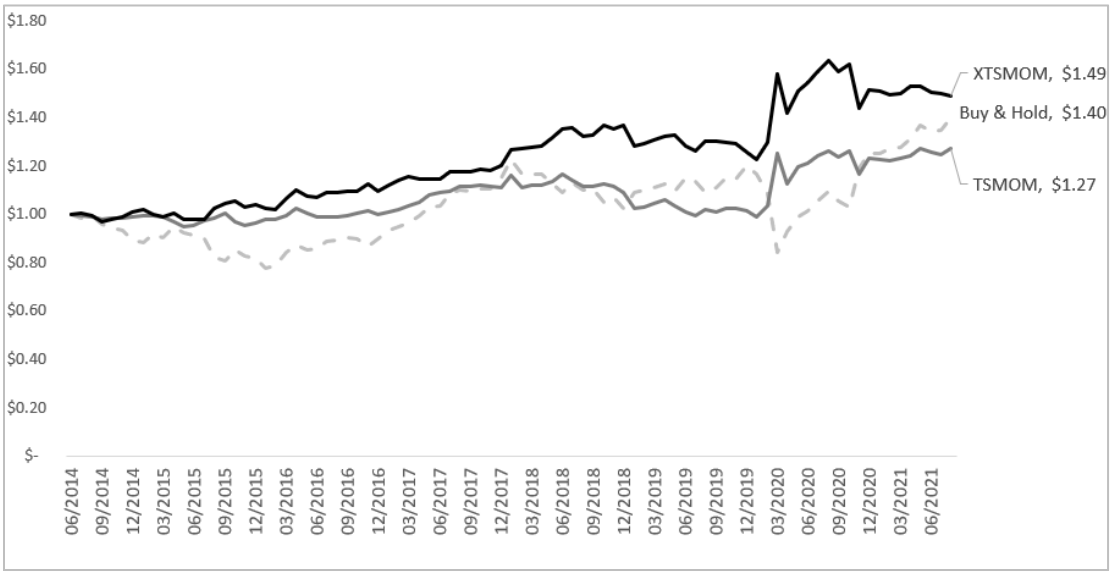
This table reports the predictability of cross-asset time series using the signs of one-month lagged equity market returns and OVX changes per country—that is, $r_t^{e,i} = \alpha + \beta^{e,i} sign(r_{t-1}^{e,i}) + \beta^{OVX,i} sign(\Delta OVX_{t-1}) + \varepsilon_t^i$ for i=1, …, N, and N is the total number of countries in our sample, for the subsample of oil-exporting countries. Newey-West corrected t-statistics are reported in square brackets. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. The sample period is from May 2007 to August 2021.

Appendix D. Future value of $1 invested in the trading strategies with alternative initial investment dates

Panel A: May 2007-June 2014



Panel B: June 2014-August 2021



The figure plots the future value of $1 invested in the buy & hold, TSMOM, and XTSMOM for all the countries with alternative initial investment dates. The strategies include the US one-month risk-free rate. The sample period is from May 2007 to June 2014 in Panel A and from June 2014 to August 2021 in Panel B.

Appendix E. Spanning tests

	Alpha (%)	*TSMOM*	*XTSMOM*	Adj R^2(%)
Panel A: All countries				
XTSMOM	0.360**	0.834***		69.66
	[2.05]	[9.52]		
TSMOM	-0.145		0.838***	69.66
	[-1.00]		[14.98]	
Panel B: Oil-importing countries				
XTSMOM	0.366**	0.817***		67.90
	[1.99]	[8.67]		
TSMOM	-0.154		0.833***	67.90
	[-0.98]		[14.12]	
Panel C: Oil-exporting countries				
XTSMOM	0.369**	0.831***		73.10
	[2.25]	[12.64]		
TSMOM	-0.146		0.881***	73.10
	[-1.02]		[23.53]	

This table reports the results of regressing the monthly returns of the XTSMOM and TSMOM portfolios on each other. The results for all countries, oil-importing, and oil-exporting countries are presented in Panels A, B, and C, respectively. Newey-West corrected t-statistics are reported in square brackets. ** and *** represent significance at the 5% and 1% levels, respectively. The sample period is from May 2007 to August 2021.

Appendix F. Subsample analysis

	USO holding policies				US economic cycle		Two halves	
	May 2007 - Dec 2008	Jan 2009 - Jun 2013	Jul 2013 - Mar 2020	Apr 2020 - Aug 2021	Recession	Expansion	Jun 2007 - Jul 2014	Aug 2014 - Aug 2021
#Obs	19	54	81	17	22	149	86	85
Panel A: All countries								
Buy & hold	-0.355	0.188	0.018	0.676	-0.232	0.203	0.050	0.100
TSMOM	0.319	0.059	0.095	0.041	0.315	0.041	0.137	0.084
XTSMOM	0.368	0.151	0.184	-0.056	0.456	0.091	0.212	0.127
Panel B: Oil-importing countries								
Buy & hold	-0.369	0.175	0.023	0.649	-0.240	0.197	0.039	0.107
TSMOM	0.317	0.041	0.088	0.038	0.293	0.033	0.125	0.077
XTSMOM	0.354	0.135	0.186	-0.051	0.443	0.084	0.197	0.130
Panel C: Oil-exporting countries								
Buy & hold	-0.312	0.223	0.006	0.717	-0.205	0.210	0.084	0.077
TSMOM	0.306	0.107	0.101	0.046	0.367	0.052	0.162	0.092
XTSMOM	0.396	0.191	0.169	-0.066	0.486	0.101	0.246	0.114

This table reports the number of month observations in each subsample (i.e., #Obs) and the Sharpe ratio of various trading strategies, such as buy & hold, TSMOM, and XTSMOM for several subperiods based on (1) USO's holding policies, (2) NBER recession vs. expansion periods and (3) splitting the sample in two halves. Statistics for all countries, oil-importing, and oil-exporting countries are presented in Panels A, B, and C, respectively.

Table 1. Descriptive statistics for the OVX changes and stock market excess returns

Country	Mean (%)	*t*-stat	Std. dev. (%)	Skew.	Kurt.	AR(1)
OVX changes	0.051	[0.07]	12.181	3.834	43.457	-0.057
All countries	0.417***	[4.98]	7.978	-0.260	6.956	0.089
Oil-importing countries	0.392***	[4.05]	7.790	-0.246	7.029	0.087
Oil-exporting countries	0.494***	[2.73]	8.519	-0.295	6.667	0.093

This table reports the descriptive statistics such as the mean, standard deviation, skewness, kurtosis, and first-order autocorrelation coefficient for the OVX changes and pooled stock market excess returns at monthly frequency. Newey-West corrected *t*-statistics are reported in square brackets. *** represents statistical significance at the 1% level. The sample period is from May 2007 to August 2021.

Table 2. Cross-asset time-series predictability

Constant	$sign(r^e)$	$sign(\Delta OVX)$	$sign(\Delta VIX)$	$sign(\Delta VIX\_CV)$	$sign(\Delta VIX\_VP)$	SMB	HML	$Adj\ R^2(\%)$
Panel A: All countries								
0.004	0.005							0.33
[0.89]	[1.52]							
0.003	0.003	-0.010***						1.79
[0.78]	[0.94]	[-3.59]						
0.003	0.002	-0.010**	-0.001			-0.102***	0.154***	3.30
[0.64]	[0.50]	[-2.11]	[-0.26]			[-2.90]	[3.55]	
0.003	0.001	-0.009*		0.002	-0.007*	-0.104***	0.153***	4.02
[0.64]	[0.29]	[-1.90]		[0.33]	[-1.70]	[-2.99]	[3.55]	
Panel B: Oil-importing countries								
0.003	0.004							0.27
[0.83]	[1.32]							
0.003	0.002	-0.010***						1.73
[0.72]	[0.76]	[-3.59]						
0.003	0.002	-0.009**	-0.001			-0.130***	0.152***	3.58
[0.61]	[0.49]	[-1.98]	[-0.29]			[-3.86]	[3.39]	
0.003	0.001	-0.008*		0.001	-0.007	-0.132***	0.152***	4.30
[0.60]	[0.26]	[-1.76]		[0.21]	[-1.62]	[-3.92]	[3.39]	
Panel C: Oil-exporting countries								
0.004	0.006**							0.49
[1.02]	[1.96]							
0.004	0.004	-0.011***						1.92
[0.92]	[1.37]	[-3.35]						
0.004	0.001	-0.011**	0.000			0.026	0.165**	3.12
[0.79]	[0.43]	[-2.36]	[-0.11]			[0.33]	[2.30]	
0.004	0.001	-0.010**		0.004	-0.008*	0.022	0.164**	3.85
[0.83]	[0.33]	[-2.22]		[0.77]	[-1.83]	[0.29]	[2.31]	

This table reports the predictability of single-asset time series using the sign of one-month lagged stock market returns (first model), and the predictability of cross-asset time series using the signs of one-month lagged stock market returns and OVX changes (second to fourth models). Panel A reports the results for all countries, while Panels B and C report the result for the oil-importing and oil-exporting countries, respectively. $sign(r^e), sign(\Delta OVX), sign(\Delta VIX), sign(\Delta VIX\_CV)$ and $sign(\Delta VIX\_VP)$ are the sign of the stock excess returns, OVX changes, VIX changes, changes in the VIX conditional variance, and changes in the VIX variance premium, respectively. SMB and HML are the one-month lagged size and book-to-market long-short portfolio returns per country. White-corrected t-statistics are clustered by year-month and reported in square brackets. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. The sample period is from May 2007 to August 2021.

Table 3. Returns by momentum regime

Panel A: TSMOM regime				
	Positive stock	Negative stock	Positive OVX	Negative OVX
#Obs	5,345	4,525	4,406	5,352
Stock market return	0.84%	-0.10%	-0.80%	1.32%
Sharpe ratio	0.12	-0.01	-0.09	0.19

Panel B: XTSMOM regime				
	Positive stock, positive OVX	Negative stock, positive OVX	Positive stock, negative OVX	Negative stock, negative OVX
#Obs	1,883	2,520	3,402	1,947
Stock market return	-0.24%	-1.21%	1.38%	1.22%
Sharpe ratio	-0.03	-0.12	0.22	0.15

This table reports the number of country-month combinations (i.e., #Obs), the average stock market excess return, and corresponding Sharpe ratios under the TSMOM and XTSMOM regimes, presented in Panels A and B, respectively. An asset is in a positive (negative) stock market regime in month t if the one-month lagged excess return of the stock market is positive (negative). Likewise, an asset is in an XTSMOM regime of positive stock returns and positive OVX changes if the one-month lagged excess return of the stock market and of OVX changes are positive, and likewise for the other regimes. The sample period is from May 2007 to August 2021.

Table 4. Performance of various trading strategies

	Mean (%)	*t*-stat	Std. dev. (%)	Sharpe ratio	Opdyke p-value	Skewness	Kurtosis
Panel A: All countries							
Buy & Hold	0.407	[0.76]	5.939	0.069	(0.194)	-0.724	6.760
TSMOM	0.520	[1.63]	4.556	0.114*	(0.053)	1.886	12.740
XTSMOM	0.794**	[2.24]	4.545	0.175***	(0.004)	2.063	12.610
Panel B: Oil-importing countries							
Buy & Hold	0.378	[0.71]	5.917	0.064	(0.420)	-0.676	6.468
TSMOM	0.472	[1.55]	4.531	0.104	(0.150)	1.620	11.961
XTSMOM	0.751**	[2.20]	4.488	0.167**	(0.014)	1.911	12.016
Panel C: Oil-exporting countries							
Buy & Hold	0.498	[0.88]	6.223	0.080	(0.318)	-0.794	7.049
TSMOM	0.669*	[1.74]	5.079	0.132*	(0.056)	1.992	11.545
XTSMOM	0.925**	[2.29]	4.934	0.188***	(0.004)	2.202	12.466

This table reports the summary statistics, such as the mean, *t*-statistic, standard deviation, Sharpe ratio, Opdyke's (2007) Sharpe ratio *p*-value (whose null hypothesis is the Sharpe ratio equals zero), skewness, and kurtosis of the excess returns of various trading strategies, such as buy & hold, TSMOM, and XTSMOM. Descriptive statistics for all countries, oil-importing, and oil-exporting countries are presented in Panels A, B, and C, respectively. Newey-West corrected *t*-statistics are reported in square brackets. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. The sample period is from May 2007 to August 2021.

Table 5. XTSMOM excess returns

Alpha (%)	$TSMOM$	MKT	SMB	HML	UMD	ΔVIX	ΔVIX_CV	ΔVIX_VP	$\Delta ILLIQ$	$Adj\ R^2$(%)
Panel A: All countries										
0.413**	0.742***	0.002	-0.045	-0.223*	-0.234**	0.670*			3.788	72.62
[2.17]	[8.56]	[0.02]	[-0.42]	[-1.94]	[-2.01]	[1.79]			[1.55]	
0.449**	0.697***	0.008	-0.020	-0.233**	-0.251**		0.121	0.324**	3.055	73.90
[2.33]	[7.73]	[0.13]	[-0.18]	[-2.11]	[-2.18]		[1.40]	[2.21]	[1.43]	
Panel B: Oil-importing countries										
0.410**	0.725***	0.004	-0.049	-0.233**	-0.236**	0.690*			3.937*	71.16
[2.06]	[7.66]	[0.06]	[-0.45]	[-1.99]	[-1.96]	[1.67]			[1.65]	
0.444**	0.677***	0.010	-0.024	-0.241**	-0.254**		0.124	0.336**	3.154	72.45
[2.21]	[6.94]	[0.15]	[-0.21]	[-2.13]	[-2.14]		[1.49]	[2.22]	[1.53]	
Panel C: Oil-exporting countries										
0.444**	0.748***	-0.009	-0.041	-0.197*	-0.236**	0.778**			3.434	75.67
[2.54]	[13.33]	[-0.15]	[-0.35]	[-1.78]	[-2.23]	[2.53]			[1.37]	
0.485***	0.718***	0.000	-0.010	-0.213**	-0.251**		0.138	0.321**	2.683	77.11
[2.77]	[11.99]	[-0.01]	[-0.08]	[-2.00]	[-2.44]		[1.29]	[2.56]	[1.16]	

This table reports regression results from Equation (5) between the excess returns of the XTSMOM on the excess returns of the TSMOM and several standard asset pricing factors {*MKT*, *SMB*, *HML*, *UMD*} for developed countries, and VIX returns and changes in its components (ΔVIX_CV and ΔVIX_VP) and $\Delta ILLIQ$. The results of the full sample, subsample of oil-importing countries, and subsample of oil-exporting countries are presented in Panels A, B, and C, respectively. Newey-West corrected *t*-statistics are reported in square brackets. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. The sample period is from May 2007 to August 2021.

Table 6. Excess returns of the XTSMOM everywhere

Alpha (%)	*TSMOM*	*MSCI_World*	*VAL_Everywhere*	*MOM_Everywhere*	*Δusd*	*Adj* R^2(%)
Panel A: All countries						
0.463***	0.794***	-0.085	-0.287	-0.095*	-0.137	70.24
[2.60]	[10.00]	[-0.51]	[-1.42]	[-1.85]	[-1.36]	
Panel B: Oil-importing countries						
0.467**	0.775***	-0.078	-0.279	-0.097*	-0.128	68.41
[2.48]	[8.91]	[-0.44]	[-1.33]	[-1.86]	[-1.20]	
Panel C: Oil-exporting countries						
0.500***	0.792***	-0.109	-0.335*	-0.124**	-0.181*	74.13
[3.06]	[13.97]	[-0.66]	[-1.76]	[-2.03]	[-1.89]	

This table reports regression results from Equation (6) between the excess returns of the XTSMOM on the excess returns of the TSMOM, the MSCI World index, the Asness et al. (2013) value, the momentum everywhere factors, and the natural log changes in the USD index. The results for all countries, oil-importing, and oil-exporting countries are presented in Panels A, B, and C, respectively. Newey-West corrected t-statistics are reported in square brackets. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. The sample period is from May 2007 to August 2021.

Table 7. Changes in oil uncertainty and funding constraints of financial intermediaries

	TED_t		$Credit_t$		BAB_t		IBI_t	
Constant	0.427***	[5.89]	2.739***	[20.78]	0.006***	[3.54]	0.001	[0.08]
ΔOVX_{t-1}	0.005	[1.51]	0.006	[1.16]	-0.001***	[-3.59]	-0.001*	[-1.65]
Adj-R^2 (%)	1.41		0.23		7.57		0.87	

This table reports regression coefficients in the predictive regression from Equation (7) between the changes in OVX on various funding constraint variables. These variables include the TED spread (TED), the Credit spread ($Credit$), the betting-against-beta factor (BAB) and the International Bank Index returns (IBI). Newey-West corrected t-statistics are reported in square brackets. * and *** represent significance at the 10% and 1% levels, respectively. The sample period is from May 2007 to August 2021.

Table 8. The impact of oil supply and demand shocks on XTSMOM returns

Alpha (%)	Supply	Agg. Demand	Oil-specific Demand	$Adj\ R^2$(%)
Panel A: All countries				
0.828***	-0.007*	-0.002	-0.007*	2.65
[2.54]	[-1.87]	[-0.45]	[-1.75]	
Panel B: Oil-importing countries				
0.783***	-0.006*	-0.002	-0.006*	2.11
[2.49]	[-1.80]	[-0.44]	[-1.67]	
Panel C: Oil-exporting countries				
0.967***	-0.008**	-0.003	-0.008*	3.79
[2.60]	[-1.96]	[-0.48]	[-1.90]	

This table reports regression results from Equation (8) between the excess returns of the XTSMOM on the crude oil supply, aggregate demand, and oil-specific demand shocks from Kilian's (2009) SVAR. The results for all countries, oil-importing, and oil-exporting countries are presented in Panels A, B, and C, respectively. Newey-West corrected t-statistics are reported in square brackets. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. The sample period is from May 2007 to August 2021.

Table 9. XTSMOM and the economy

Panel A: TSMOM regime

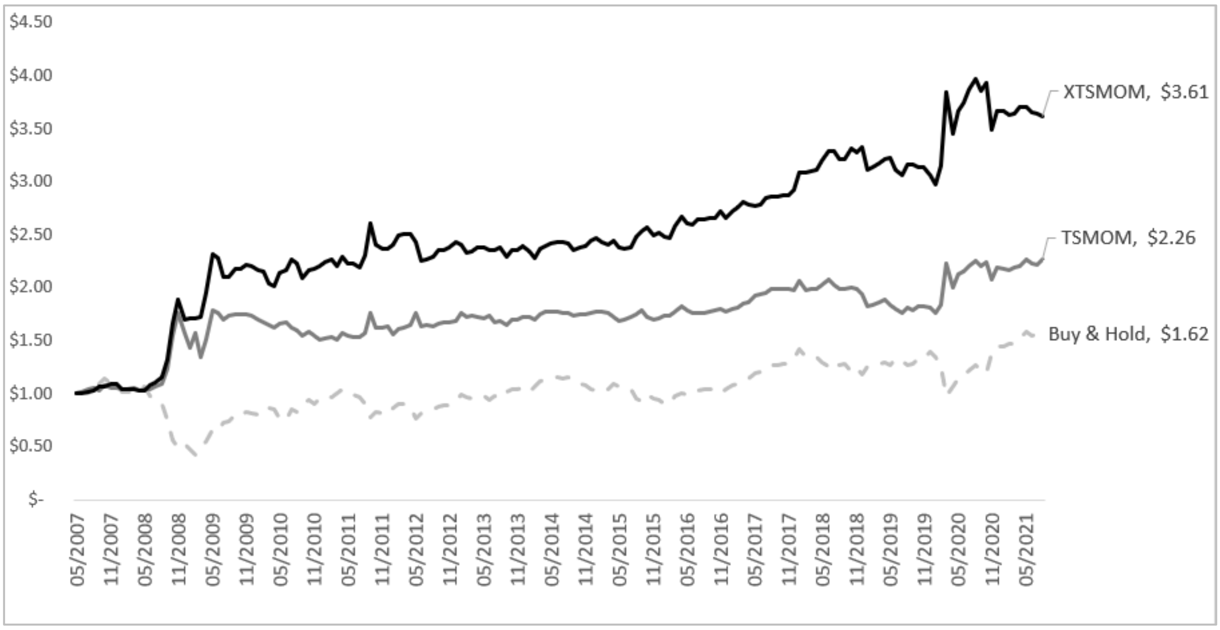
	Positive stock		Negative stock		Positive OVX		Negative OVX	
	Average	#Obs	Average	#Obs	Average	#Obs	Average	#Obs
IP (bps)	17.197	4,405	2.211	3,810	-1.192	3,755	19.766	4,547
Unemployment (bps)	-1.448	4,136	24.119	3,549	26.495	3,473	-2.419	4,211
Inflation (bps)	-1.776	4,855	-0.48	4,228	-0.139	4,104	-1.675	4,979

Panel B: XTSMOM regime

	Positive stock, positive OVX		Positive stock, negative OVX		Negative stock, positive OVX		Negative stock, negative OVX	
	Average	#Obs	Average	#Obs	Average	#Obs	Average	#Obs
IP (bps)	2.537	1,553	25.249	2,841	-3.968	2,134	10.560	1,633
Unemployment (bps)	7.301	1,468	-6.118	2,668	40.541	2,006	3.976	1,543
Inflation (bps)	-4.05	1,713	-0.304	3,142	2.664	2,391	-4.025	1,837

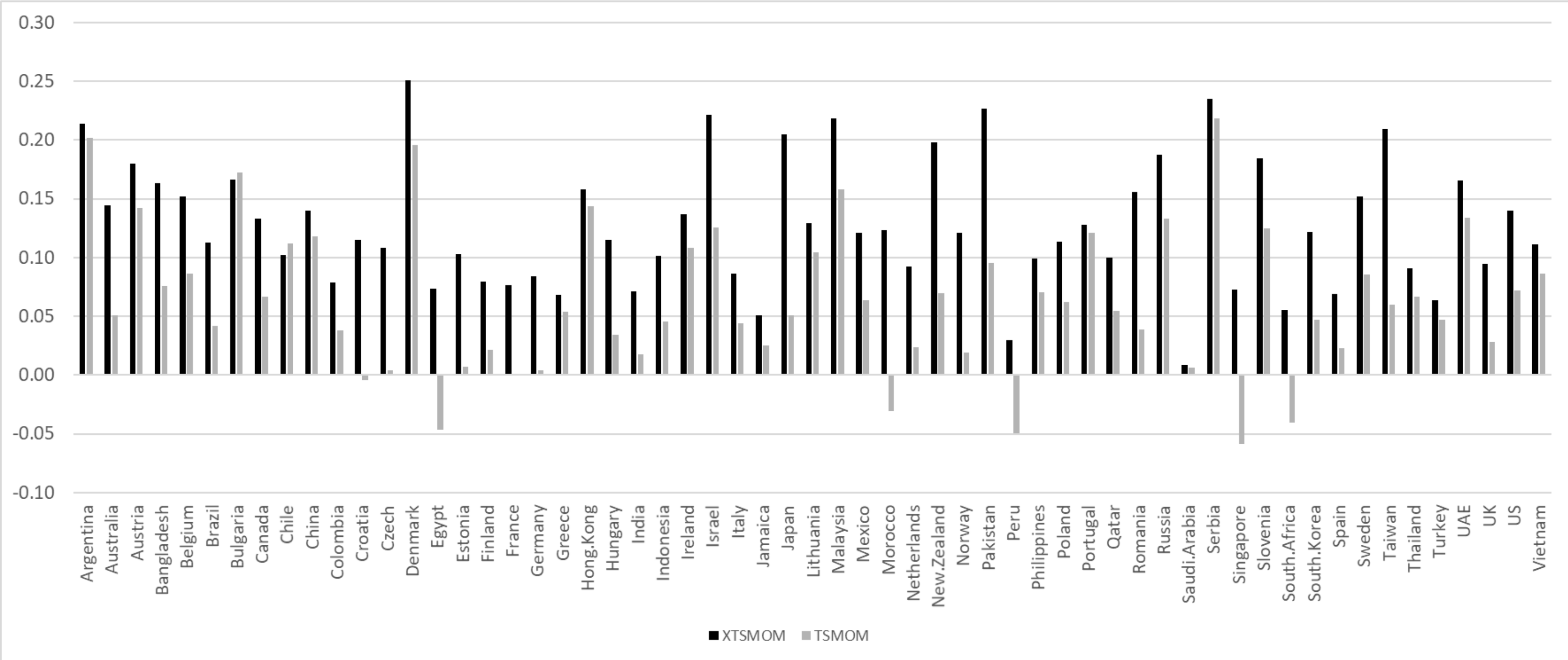
This table reports the number of country-month combinations (i.e., #Obs), the average next-12-month changes in industrial production (i.e., IP), the unemployment and inflation in basis points under the TSMOM and XTSMOM regimes, presented in Panels A and B, respectively. An asset is in a positive (negative) stock regime in month *t* if the one-month lagged excess return of the stock market is positive (negative). Likewise, an asset is in an XTSMOM regime of positive stock returns and positive OVX changes if the one-month lagged excess return of the stock market and that of OVX changes are positive. The sample period is from May 2007 to August 2021.

Figure 1. Future value of $1 invested in the trading strategies



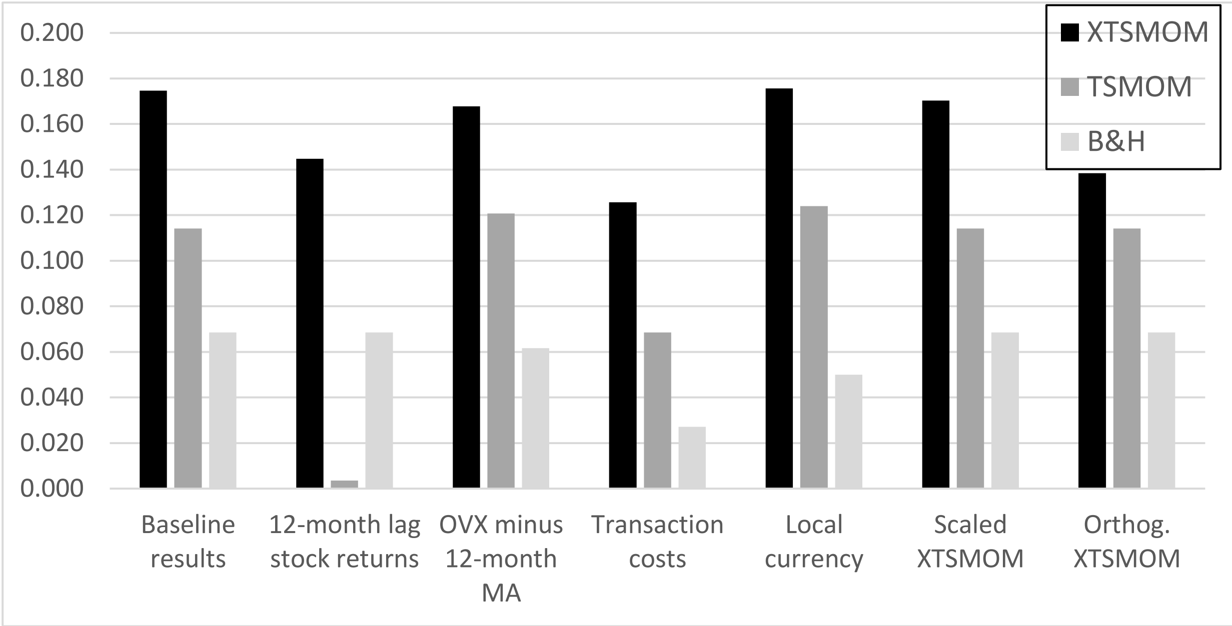
This figure plots the future value of $1 invested in the buy & hold, TSMOM, and XTSMOM strategies for all the countries in May 2007. The strategies include the US one-month risk-free rate. The sample period is from May 2007 to August 2021.

Figure 2. Sharpe ratios of the XTSMOM and TSMOM by country



This figure plots the Sharpe ratios of the XTSMOM and the TSMOM for each country. The sample period is from May 2007 to August 2021.

Figure 3. Robustness tests for the XTSMOM strategy



This figure plots the Sharpe ratios for all the countries with the buy & hold, TSMOM, and XTSMOM trading strategies. We show the baseline results as well as the XTSMOM based on (1) the past 12-month mean stock return as the stock return signal, (2) using the difference between the level of OVX and its 12-month moving average as the oil uncertainty signal, (3) with the transaction costs of Angelidis and Tessaromatis (2017), 4) the stock market excess returns in local currency, (5) the scaled XTSMOM (see, e.g., PSV, 2020), and (6) after orthogonalizing the OVX series. The sample period is from May 2007 to August 2021.

Figure 4. The XTSMOM and TSMOM smiles

The figure plots the monthly excess returns of the TSMOM and XTSMOM against the corresponding monthly excess returns of the developed stock market portfolio from Kenneth French's website. We also plot the second-order polynomial trendlines for the TSMOM (dashed black line) and the XTSMOM (dotted gray line) monthly returns. The sample period is from May 2007 to August 2021.