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Oil-Price Uncertainty and International Stock Returns: Dissecting Quantile-Based Predictability and Spillover Effects Using More than a Century of Data

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OIL-PRICE UNCERTAINTY AND INTERNATIONAL STOCK RETURNS: DISSECTING QUANTILE-BASED PREDICTABILITY AND SPILLOVER EFFECTS USING MORE THAN A CENTURY OF DATA

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ABSTRACT

We investigate whether oil-price uncertainty helps in forecasting international stock returns of ten advanced and emerging countries. We consider an out-of-sample period of 1925:08 to 2021:09, with an in-sample period 1920:08-1925:07, and employ a quantile-predictive-regression approach, which is more informative relative to a linear model, as it investigates the ability of oil-price uncertainty to forecast the entire conditional distribution of stock returns, rather than only its conditional-mean. A quantile-based approach accounts for non-linearity (including regime changes), non-normality, and outliers. Based on a recursive estimation scheme, we draw the following main conclusions: the quantile-predictive-regression approach using oil-price uncertainty as a predictor statistically outperforms the corresponding quantile-based constant-mean model for all ten countries at certain quantiles (capturing normal, bear, and bull markets), and over specific forecast horizons, compared to forecastability being detected for eight countries under the linear predictive model. Moreover, we detect forecasting gains in many more horizons (at particular quantiles) compared to the linear case. In addition, an oil-price uncertainty-based state-contingent spillover analysis reveals that the ten equity markets are tighter connected during the upper regime, suggesting that heightened oil-market volatility erodes the benefits from diversification across equity markets.

JEL Codes: C22; C53; G15; Q41

Keywords: international stock markets; oil price uncertainty; forecasting; quantile regression

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1. INTRODUCTION

The large literature on investment under uncertainty and real options suggests that high oil-price uncertainty creates cyclical fluctuations in investment by lowering firms' incentive for current investment (Bernanke, 1983; Pindyck, 1991). This, in turn, impacts cash flows generated by a firm and the discount rate that is used to calculate stock prices and, hence, negatively impacts stock prices and/or returns (Swaray and Salisu, 2018). In addition, because stock prices are the sum of discounted cash flows including dividends, oil-price uncertainty can adversely affect stock prices by decreasing the overall profit that a firm generally uses to pay dividends, with this resulting from the fact that firms need to bear additional costs to avoid risk associated with oil-price uncertainty (Demirer et al., 2015).[1] Overall, the theoretical prediction is that oil-price uncertainty negatively impacts stock prices and/or returns via the investment and dividends channels, with this hypothesis having been widely empirically validated for both developed economies (see, Sadorsky (1999), Masih et al., (2011), Alsalman (2016), Diaz et al., (2016), Rahman (2021)) and emerging countries[2] (see, Jiranyakul (2014), Aye (2015), Bass (2017), Benavides (2019)).[3]

Given that in-sample tests of predictability might not translate into out-of-sample gains, we aim to extend the empirical literature on the nexus between oil-price uncertainty and stock markets by analysing the role of West Texas Intermediate (WTI) crude-oil-price volatility (traditionally used in the above-mentioned literature as a metric for oil-price uncertainty) for the stock returns of Canada, France, Germany, India, Italy, Japan, South

[1] Furthermore, in the wake of the recent financialization of the oil market post the Global Financial Crisis, Christoffersen and Pan (2018) suggests that an increase in oil price volatility signal higher economic uncertainty and the tightening of funding constraints for financial intermediaries, which are systematic factors in the stock market.

[2] Basher and Sadorsky (2006) employed a multi-factor model to show that oil-price risk tends to strongly affect a large set of emerging-stock_market returns.

[3] See also the working paper of Salisu and Gupta (2021), which validates the negative relationship between oil uncertainty and stock prices in a global vector-autoregressive model for a set of 26 advanced and developing countries covering 90% of the world Gross Domestic Product (GDP).

Africa, Switzerland, the United Kingdom (UK), and the United States (US) over the monthly period from 1920:08 to 2021:09. From a statistical perspective, such a forecasting analysis is important because it is deemed as a more robust test of predictability compared to an in-sample analysis (Campbell, 2008). Because we use in our empirical analysis the longest available data sample, we avoid the issue of a possible sample-selection bias. At the same time, we also cover extreme fluctuations in the oil price associated with a wide-range of historical events involving the interwar period, the Great Depression, the Korean and Vietnam wars, the two oil shocks, the Gulf war, the 9/11 attack, the Iraq invasion, the Global Financial Crisis, the Arab Spring, the oil-price collapse of 2014-2016, the US-China trade war, and, of course, the more recent swings in the price of oil due to the outbreak of the COVID-19 pandemic. The focus on the G7 countries and Switzerland, besides the early-established stock markets of two emerging economies, is purely driven by the availability of data on stock prices over this long sample period. Moreover, our decision to analyze the stock markets of these ten (advanced and emerging) economies is motivated by their importance in the global economy, with these countries representing nearly two-third of global net wealth, and nearly half of world output (Salisu et al., 2021). Naturally, the impact of oil-price uncertainty on the equity-market system of these economies would translate into a global effect.

Besides the statistical validation of the role of oil-price uncertainty for stock returns based on a full-fledged out-of-sample forecasting experiment, the empirical results we document in this research also possess value for investors, academics, and policymakers. For instance, practitioners in finance require real-time forecasts of stock returns for asset allocation, while academics are particularly interested in stock-returns forecasts because they hold important lessons for measures of market efficiency, and also help to refine asset-pricing models (Rapach and Zhou, 2013). Moreover, it is well-established that stock returns serve as

a leading indicator for macroeconomic variables (Stock and Watson, 2003), and the accurate forecasting of stock returns would entail valuable information to policymakers in terms of designing optimal policy responses to oil price uncertainty.

Naturally, the existing literature on forecasting international stock returns, based on a wide array of (linear and nonlinear) models and (macroeconomic, financial, technical and behavioral) predictors, is vast, to say the least. Hence, providing a detailed review is beyond the scope of this paper, and also not our main objective, but the interested reader is referred to the recent works of Rapach et al., (2013), Aye et al., (2017), Gupta et al., (2017, 2020), Huber et al., (2017), Jordan et al., (2017, 2018), Christou et al., (2021), Salisu and Gupta (2021), and Rapach and Zhou (forthcoming), to get an idea about this ever burgeoning area of research. Even though the role of the oil price and/or returns in forecasting stock returns has been extensively analysed (see, Narayan and Gupta (2015), Gupta and Wohar (2017), Degiannakis et al., (2018), Smyth and Narayan (2018) for detailed reviews), our contribution to this important and significant area of research is that we are the first to incorporate the role of oil-price uncertainty in forecasting international stock returns of advanced and emerging countries using over a century of data.

At this stage, it is important to outline the econometric approach we rely on to conduct our forecasting experiment. Traditionally, as discussed in detail in the papers cited above, the literature on predicting stock returns has relied on linear models, but, more recently, the focus has shifted to developing models that accommodate for the well-established nonlinear relationship between stock returns and its predictors (see the discussions in Guidolin et al., (2009), Gupta and Majumdar (2016), Demirer et al., (2017), Gupta et al., (2018, 2019), among others). Against this backdrop, we not only consider the standard linear predictive-regression approach, but also use a predictive quantile-regression approach for our forecasting analysis. We argue that, due to non-linearity and non-normality patterns, which

we show to exist in an overwhelming fashion in our dataset based on formal statistical tests, a linear regression approach might not be adequate for exploring the ability of oil-price uncertainty to forecast the entire distribution of the stock returns of the ten countries.

The quantiles-based approach, as originally developed by Koenker and Bassett (1978), enables us to have a more complete characterization of the forecastability of the entire conditional distribution of stock returns through a set of conditional quantiles, rather than only its conditional mean, as is the case with the standard linear regression approach. Looking at just the conditional mean of stock returns is likely to ‚hide' interesting characteristics, as it can lead us to conclude that a predictor, in our case oil-price uncertainty, has poor forecasting performance, while it is actually valuable for forecasting certain parts of the conditional distribution of stock returns. In addition, business cycle fluctuations are likely to induce the slope coefficients associated with the predictor to vary across quantiles (Meligkotsidou et al., 2014), to the extent that oil-price uncertainty may contain significant information for the lower or upper quantiles, but not for the whole conditional distribution of stock returns. The quantile-predictive regression approach, which allows us to integrate this information, would, thus, lead to additional benefits over the standard linear and other popular nonlinear approaches.

Furthermore in terms of modelling non-linearity, on the one hand, unlike the Markov-switching and the smooth threshold models, we do not need to specify number of regimes of stock returns (for instance, bear and bull) in an ad hoc fashion with the quantile -based approach. On the other hand, the quantile approach has added advantages over the non- or semi-parametric, neural networks, and time-varying approaches, as we can study each point of the conditional distribution characterizing the state of the stock market. Because the quantile-based approach studies the entire conditional distribution, which captures various states of the stock market, it adds an inherent time-varying component to the estimation

process. Though, by pursuing a recursive estimation of both the conditional-mean and predictive quantile-based approaches over the out-of-sample period, we make both the models have time-varying parameters in the forecast evaluation part of the sample, and, in the process, do not provide the quantiles-based approach with an upper-hand in terms of estimation, besides its inherent advantage of being able to provide information on the entire conditional distribution of stock returns.

In sum, the quantile-based approach is more efficient and more robust than the linear approach, which focuses on the conditional mean only, in the presence of non-normality, non-linearity, and outliers (Gebka and Wohar, 2019), with the latter possibly leading to the emergence of regime changes in the relationship between oil-price uncertainty and stock returns (which, unsurprisingly, given the usage of over a century of data, we show to exist in our sample based on tests of multiple structural breaks). The fact that the quantile-based approach is not sensitive to outliers is particularly important in our forecasting context, as this implies that the quantile forecasts are still accurate in the presence of large positive or negative returns in the sample and, therefore, the produced forecasts are robust.

To the best of our knowledge, this is the first paper to analyze the role of oil-price uncertainty in forecasting the historical stock returns of ten advanced and emerging countries spanning over 100 years of monthly data. In addition to this, while the focus is on forecasting, to provide an angle of economic and investment implications of our results, we also conduct an analysis involving regimes-dependent (smooth-transition, besides threshold, Markov-switching, and quantiles-based) methods of connectedness of the ten stock markets, with the regimes contingent on the high- and low-levels of oil-price uncertainty. In the process, we test the so-called correlation-asymmetry phenomena reported in a number of studies (see Das et al., (2019) for a detailed review), that refer to the asymmetric pattern in which stock returns tend to be more correlated (connected) during bear-market regimes (as well as during periods

of extreme price fluctuations). This is likely to be the case when oil-price uncertainty is high, given the theoretical and empirical evidence of the negative nexus between stock returns and a highly volatile oil market. Understandably, if connectedness is high across the ten markets when oil uncertainty is in its upper regime, then clearly portfolio diversification opportunities across international equity markets are likely to erode, with all the stock returns experiencing a bearish-phase.

We organize the remainder of our paper as follows. In Section 2, we describe the methodologies we use in our empirical analysis. In Section 4, we discuss the data and our empirical results, and in Section 4, we conclude.

2. Predictive Regression Models

The classical linear predictive mean-regression model is given by:

$$r_{t+h} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{t+h} \tag{1}$$

where r_{t+h} is the observed cumulated stock returns over time period t+1 to t+h, $x_{i,t}$ is a specific regressor / predictor at time t, which in our work is oil-price uncertainty, and ε_{t+h} is the error term assumed to be independent with zero mean and variance σ^2. The ordinary least squares (OLS) estimators, $\hat{\alpha}_i, \hat{\beta}_i$, of the parameters in the predictive mean-regression model are estimated by minimizing the quadratic expected loss, $\sum_{t=0}^{T-1}(r_{t+h} - \alpha_i - \beta_i x_{i,t})^2$, with respect to the parameters, α_i, β_i. The point forecast of stock returns at time $t + h$, is obtained as: $\hat{r}_{i,t+h} = \hat{\alpha}_i + \hat{\beta}_i x_{i,t}$.

The aforementioned model is primarily devised to predict the mean of r_{t+h}, and not the entire conditional distribution of stock returns. Koenker and Bassett (1978) showed that quantile-regression estimators are more efficient and robust than mean regression estimators in cases where nonlinearities and deviations from normality exist, with both these features

existing in our data (as discussed below). Hence, we consider the predictive quantile-regression model of the following form:

$$r_{t+h} = \alpha_i^{(\tau)} + \beta_i^{(\tau)} x_{i,t} + \varepsilon_{t+h} i = 1, \dots, N, \quad (2)$$

where $\tau \in (0,1)$, and ε_{t+h} is assumed independent derived from an error distribution $g_\tau(\varepsilon)$ with the τ-th quantile equal to 0. Model (2) implies the τ-th quantile of r_{t+h} given $x_{i,t}$, is $Q_\tau(r_{t+h}|x_{i,t}) = \alpha_i^{(\tau)} + \beta_i^{(\tau)} x_{i,t}$, where the intercept and the coefficients depend upon τ. The estimators of the parameters of the predictive quantile-regression model in Eq. (2), $\alpha_i^{(\tau)}, \beta_i^{(\tau)}$, are obtained by minimizing the sum $\sum_{t=0}^{T-1} \rho_\tau(r_{t+h} - \alpha_i^{(\tau)} - \beta_i^{(\tau)} x_{i,t})$, where the so called check function is being used, $\rho_\tau(u) = u(\tau - I(u < 0)) = \frac{1}{2}[|u| + (2\tau - 1)u]$. The forecast of the τ-th quantile of the distribution of stock returns at time $t + 1$ is $\hat{r}_{i,t+h}(\tau) = \hat{\alpha}_i^{(\tau)} + \hat{\beta}_i^{(\tau)} x_{i,t}$.

3. Data And Empirical Results

3.1. Data

The stock-index raw data are denominated in respective local currencies for Canada (S&P TSX 300 Composite Index), France (CAC All-Tradable Index), Germany (CDAX Composite Index), India (Bombay Stock Exchange (BSE) Index), Italy (Banca Commerciale Italiana Index), Japan (Nikkei 225 Index), South Africa (Johannesburg Stock Exchange All Share (JSE-ALSI) Index), Switzerland (All Share Stock Index), the UK (FTSE All Share Index), and the US (S&P500 Index). The local currency stock indexes of the nine countries (except for the US) are converted to US dollars by using the bilateral dollar-based exchange rates, and then divided by the US Consumer Price Index (CPI), to get to the real stock prices.

The WTI oil price in US dollars is also deflated by the US CPI to get the corresponding real oil price. All our raw data are obtained from the Global Financial Data.[4]

We then compute log-returns in percentages for the stock and oil prices. Following the early work of Sadorsky (1999), and the extant literature on oil-price uncertainty, we fit a Generalized Autoregressive Conditional Heteroskedasticity (GARCH(1,1)) model[5] to obtain the conditional variance of the log-returns of oil, which in turn serves as our metric of oil-price uncertainty (*OIL_UNC*). Based on a balanced data set, our monthly sample period covers the period from 1920:08 to 2021:09, at the time of writing of this paper.

Figure A1 at the end of the paper (Appendix) plots the stock-market returns and the GARCH(1,1)-based oil-price conditional volatility (*OIL_UNC*). In addition, as can be seen from the summary statistics of the variables reported in Table A1 (Appendix), all the ten stock log-returns and *OIL_UNC* are found to be non-normal based on the rejection of the null hypothesis of normality under the Jarque-Bera test at the highest level of significance. Heavy tails of the variables under consideration provide a preliminary motivation to look at a predictive quantile-based approach.

3.2. Empirical Findings

3.2.1. Forecasting Results

We use an in-sample period from 1920:08 to 1925:07 (i.e., 60 months), and then the models in Eq. (1) and Eq. (2) are estimated recursively over the out-of-sample period from 1925:08 to 2021:09, to produce forecasts at horizons (*h*) of 1- ,3- ,6- ,9-, 12, 18-, and 24-month-ahead. The choice of this in-sample period ensures that all regime changes, as determined by the multiple structural break tests of Bai and Perron (2003) applied to Eq. (1) and reported in Table A2, fall over the out-of-sample period. In this manner, given the

[4] https://globalfinancialdata.com/.

[5] Complete details of the estimation results of the GARCH(1,1) model are available upon request from the authors.

recursive estimation of both the predictive linear and predictive quantile-based regressions, we ensure that the latter does not enjoy any unfair advantage in terms of being inherently a nonlinear model, with non-linearity at least arising because of structural breaks. Non-linearity in the relationship between stock returns and *OIL_UNC* is overwhelmingly confirmed by the Brock et al., (1996, BDS) test when applied on the residuals of Eq. (1), with the test rejecting the null hypothesis of *i.i.d.* at all possible dimensions at the highest possible level of significance, as shown in Table A3. The results from the structural instability analysis as well as the non-linearity test, highlight, on the one hand, the inappropriateness of the linear predictive regression model given in Eq.(1), and, on the other hand, indicate the necessity to employ a predictive quantile-based approach, as in Eq. (2), when forecasting stock returns based on the information content of *OIL_UNC*.

[Please insert Table 2]

In any event, for the sake of completeness and comparability, we also present the forecasting results from the predictive linear regression model in Table 1, besides the same from the predictive quantile-based approach, where we use the following quantiles for the latter:τ = 0.10, 0.20, 0.30….0.90. The entries in the table report the ratio of the Mean Square Forecast Errors (MSFEs) of equation (1) relative to the same of the constant-mean (random-walk (RW)) model, i.e., $\hat{r}_{i,t+h} = \hat{\alpha}_i$, and the same for equation (2) relative to the quantiles-based RW model, i.e., $\hat{r}_{i,t+h}(\tau) = \hat{\alpha}_i^{(\tau)}$. Understandably, if the ratio is less than one, then the model with the predictor outperforms the model without it. It is also important, however, to test whether the superior performance of the model with the *OIL_UNC*, if it holds, is statistically different from the corresponding benchmark. Given that the model featuring oil-price uncertainty nests its associated benchmark, we use the *MSE-F* test statistic[6] of

[6] $MSE\text{-}F=(MSFE_R/MSFE_{UR}-1)\times(T-R-h+1)$, where $MSFE_R$ and $MSFE_{UR}$ are the mean square forecast error of the restricted (without *OIL_UNC*) and unrestricted (with *OIL_UNC*) models, respectively, with *T* being the total

McCracken (2007) to check whether, in cases where the ratio is less than one, the model with oil-price uncertainty outperforms the one without it in a significant fashion.

At this point, it is worthwhile to emphasize that, because we use the MSFE to evaluate forecast errors, we assume that a forecast consumer uses a squared-error loss function to study the predictive performance of both the linear-regression and the quantiles-based approach. Alternatively, one could use a quantile-based loss function (that is, the check function), to evaluate the forecast errors implied by the quantile-based approach. This quantiles-based loss function is asymmetric (except in the special case where the conditional median is being analyzed) and accounts for the fact that the quantile-regression model adjusts forecasts of stock returns upward or downward depending on the quantile under scrutiny (see, for example, Pierdzioch et al., (2014, 2016); Gupta and Pierdzioch (2022)). In this paper, we stick to the standard quadratic loss function (which has been used in recent research in a quantile-regression context by, for example, Ren et al., (2022)) because using the MSFE for both approaches ensures that the results for the forecast evaluations are comparable across the two different approaches. From the perspective of a forecast consumer, the upward and downward adjustments of forecasts made under the quantile-based approach can then be interpreted as a data-driven pragmatic attempt to explore potential improvements in the forecasting performance of oil-price uncertainty by moving from a linear to a quantiles-based forecasting approach, where the underlying *ceteris-paribus* assumption is that the squared-error loss function and, thus, the preferences of a forecast consumer are the same for both approaches.

As can be seen from Table 1, for the predictive linear-regression model, the model with *OIL_UNC* beats the benchmark model in terms of forecasting performance in 13

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sample size, R the length of the in-sample, and h the forecast horizon under consideration. A positive and significant *MSE-F* indicates that the forecasts from the unrestricted model are statistically superior to those from the restricted model. Given our set-up, the 1%, 5% and 10% critical values derived from Table 4 of McCracken (2007; pp. 732) are 3.951, 1.518 and 0.616 respectively.

instances, which happens to be the cases at: h = 1 and 6 for Canada; h = 24 for France, India, Japan, and Switzerland; h = 9 for Germany; h = 6, 9 and 18 for the UK, and; h =1, 3 and 6 for the US. There is no evidence of stock-returns forecastability due to *OIL_UNC* for Italy and South Africa at any of the seven forecasting horizons considered. But, more importantly, out of the 13 cases where the model with *OIL_UNC* outperforms the benchmark, the forecasting gains, based on the *MSE-F* test, are statistically significant at the 1% level in nine cases, 5% in three cases, and 10% in the remaining one case. In general, the evidence is mixed, with forecastability primarily observed at medium- to long-horizons for oil importers (France, Germany, India, Japan, Switzerland, and the UK), and at shorter-horizons for oil exporters such as Canada and the US.

Given the evidence non-normality and non-linearity (including structural breaks), however, these results are perhaps not surprising, besides being unreliable. Thus, we move on to the predictive quantile-based approach. For Canada, significant forecastability based on the information content of *OIL_UNC* is observed for at least one conditional quantile particularly at the lower end (i.e., τ = 0.30, 0.50-0.60 and 0.80 at h = 3; 0.10-0.40 and 0.70-0.90 at h = 6; 0.10-0.30 at h = 9, and; τ = 0.10-0.20 at h = 12 and 18) over all forecast horizon, except for h=24. Hence, stronger predictive effect, in terms of the coverage of the quantiles, is observed at lower forecast horizons. For France, strong forecastability is observed at h = 24 over the conditional median and beyond, i.e., τ = 0.50 to 0.90, but the *OIL_UNC* also plays a role in predicting a bearish market (i.e., τ = 0.10 at h = 9, 12, 18, and; τ = 0.20 at h = 9 and 12). For Germany, while forecastability is observed for τ = 0.2-0.4 at h = 1, and at τ = 0.4 at h = 6, the same is observed at primarily higher conditional quantiles (i.e., τ = 0.60-0.70 for h = 12, and 0.70-0.80 for h = 18. For India, while we could not find evidence of forecastability at the shortest horizon (h = 1), it is indeed observed primarily at higher quantiles (i.e., 0.70 onwards up to 0.90) for h = 3 to 18, with the strongest predictability observed at h = 24

covering virtually the entire conditional distribution (i.e., τ = 0.10 to 0.80). Compared to the predictive linear-regression model, under which Italian and South African stock returns were completely unpredictable based on the information content of *OIL_UNC*, now with the quantile-based approach, stock returns for Italy are consistently forecastable over all seven horizons considered for at least one conditional quantile, and, in particular, for below the median (τ = 0.10-0.40). Moderately higher quantiles are also predictable at h = 1 and 24. A story similar to that for Italy also holds for South Africa, with higher conditional quantiles (τ = 0.60-0.90) being forecastable at h = 1, 18 and 24, besides the lower quantiles (τ = 0.10-0.40) at h = 1 to 18. Turning next to Japan, barring h = 18, oil- price uncertainty can forecast at least one conditional quantile of stock returns (primarily around the median and at τ = 0.90) for the remaining forecast horizons, with the broadest evidence in terms of quantile-coverage (τ = 0.20-0.90) at h = 24. For Switzerland, forecastability of stock returns is observed at all seven horizons considered for at least one conditional quantile, with the largest quantile coverage, just as in the case of Japan, being at h = 24 (τ = 0.30-0.90). The other horizons depict forecastabilty at each end of the conditional distribution, except for h = 18, where the benchmark is outperformed at τ = 0.60. For the UK, the exception is h = 1 and 24, otherwise, for all other horizons at least two conditional quantiles are forecastable due to *OIL_UNC*, especially on and around the moderate quantiles below the median. At h = 18, the coverage of the predictable τ is equal to 0.10-0.80. Finally for the US, at least one conditional quantile of stock returns can be accurately forecasted based on the information contained in *OIL_UNC* at: h = 1, 3, 6, 12 and 18, especially in the bearish phase, though the normal market condition and the bullish-regime (i.e., τ = 0.50-0.90) is also forecastable at h = 1 to 6-month-ahead. For all the significant cases (with 3 instances of insignificance, even though the benchmark model was outperformed) of out-of-sample predictability detected under the quantile regression, 3

cases carry significance at the 5% level and 4 at the 10% level, with the rest being at the 1% level.

In sum, despite heterogeneity of the results across the stock markets, the quantile regression model with *OIL_UNC* as a predictor outperforms the prevailing quantile benchmark for all ten countries at certain quantiles, capturing normal, bear, and bull markets, over specific forecast horizons. This is unlike in the case of the predictive linear-regression model, which picks up forecasting gains for eight countries (excepting Italy and South Africa). Moreover, we unveil forecasting gains in many more horizons (at particular quantiles) compared to the linear case. Clearly, our results depict the advantages of resorting to a non-linear approach that renders it possible to shed light on the entire conditional distribution of stock returns rather than just the conditional mean, while analysing the predictive relationship of oil-price uncertainty for international stock returns, which depict non-normality. Besides the statistical importance of our findings, indeed our results also hold value for academics, investors, and policymakers seeking to optimize their respective decisions during bull, bear, and normal stock-market phases in the wake of changes in oil-price uncertainty.

Table A4 provides the results for the forecasting experiment when we use an in-sample period of 120 months, i.e., from 1920:08 to 1930:07, with 1930:08 to 2021:09 being the out-of-sample period. As can be seen from this table, the basic conclusions derived for the shorter in-sample period from 1920:08 to 1925:07, as reported in Table 1, continue to hold also for the longer in-sample period. This observation shows that our forecasting results are robust relative to a reasonable variation of the length of the in- and out-of-sample periods, in terms of the superiority of the quantile predictive regression relative to its linear counterpart.

[Please insert Table 1]

3.2.2. Regimes-Based Connectedness Results And Investment Implications

Table 2 displays the regime-dependent connectedness metrics, based on a smooth transition vector autoregressive (STVAR) model (see Balcilar et al., 2020, 2021a, b), computed in the same way as in Diebold and Yilmaz (2012). The lag order of the STVAR models is 1, which is determined by the Bayesian information criterion (BIC) in a linear VAR model. Oil uncertainty is the threshold variable. The lower regime relates to the below threshold (low uncertainty) periods, while the upper regime corresponds to the above threshold (high uncertainty) periods. The estimations for STVAR smoothness and threshold parameter are 44.876 and 59.709, respectively. The Diebold-Yilmaz spillover index as a measure of the total connectedness measure is estimated as 62.60% in the low oil-price - uncertainty regime, while it is 83.58% in the high oil-price-uncertainty regime. Thus, there is a much stronger connectedness in the high-uncertainty regime, where more than four-fifth of the total spillover is due to cross links across the stock markets and oil-price uncertainty. Indeed, much of the cross links in both regimes is with the oil-price uncertainty. In the low-uncertainty regime, Canada, France, Germany, India, Italy, the UK, and the US are significantly influenced by the oil market as volatility receivers. There are also a few strong connectedness links among stock markets in the low-uncertainty regime. For example, the spillover from Canada, Franca, Germany, Italy, and the US to Switzerland, as well as the spillover from India, the UK, and the US to South Africa are substantial. A similar pattern is also observed in the high-uncertainty regime.

In the high-uncertainty regime, the predictive power of oil-price uncertainty is stronger for almost all stock markets except South Africa. Indeed, the spillover estimates from oil-price uncertainty to stock returns are all above 90% for Canada, France, Italy, Japan, Switzerland, the UK, and the US, while they are above 80% for Germany and India. Although oil-price uncertainty is the key predictor variable for all stock returns in both regimes, its

predictive capacity is much higher in the high-uncertainty regime. In the high-uncertainty regime, 95.53% of the spillover received by the 10 stock markets comes from oil-price uncertainty, while this figure is only 70.68% in the low-uncertainty regime. Comparing the total spillover across the regimes, we observe that 88.93% of the total spillover of 11,000 in the high-uncertainty regime is accounted for by oil-price uncertainty, while this proportion falls to 53.32% in the low-uncertainty regime. Another noteworthy result for both regimes is related to the net-spillover estimates. In both regimes, all 10 stock markets are net receivers, while oil-price uncertainty is the only net transmitter. All stock markets receive higher spillover from others in the high-uncertainty regime. For example, the net spillovers received by South Africa, Japan, Germany, and India are 2.18, 1.65, 1.63, and 1.31 times higher in the high-uncertainty regime, respectively, compared to the low-uncertainty regime. A further observation is that oil-price uncertainty does not receive any spillover from stock returns in the high-uncertainty regime, while the spillover from others to oil-price uncertainty in the low uncertainty regime is also negligible.

[Please insert Table 2]

Overall, oil-price uncertainty is the key variable governing and generating spillover connectedness for the ten stock markets, where its influence is much higher during high-uncertainty periods. The main findings from the STVAR model are summarized in the network analysis provided in Figure 1.

In addition, it should be noted that the conclusions from the STVAR model are also verified in a robust manner in Tables A5, A6 and A7, under the Threshold VAR (TVAR), Markov-switching VAR (MSVAR) and Quantile VAR (QVAR), respectively (see, Shahzad et al., (2021), Balcilar et al., (2022) for further details). Our findings related to connectedness, thus, suggest that international portfolio allocation across stock markets would be relatively

more difficult during episodes of heightened oil-price uncertainty, which is likely to result in bearish stock markets[7] – a finding in line with the correlation asymmetry phenomena.

[Please insert Figure 1]

4. Conclusions

The importance of accurate forecasting of stock returns for academics and practitioners in finance, and policymakers is well-recognized. However, stock-return forecasting is highly challenging because it inherently contains a sizable unpredictable component. Naturally, a large variety of models and predictors has been used in earlier literature.

In this regard, given that in-sample predictability does not necessarily translate into out-of-sample forecasting gains, we aim to extend the structural analyses-type literature on the oil-price uncertainty/stock-returns nexus by forecasting real stock returns of ten developed and emerging markets (Canada, France, Germany, India, Italy, Japan, South Africa, Switzerland, the UK, and the US) based on the information content of oil-price uncertainty. We investigate the forecastability of the stock returns of these markets based on over a century of monthly historical data (1920:08 to 2021:09), and rely on a predictive quantile-based approach to account for non-linearity and non-normality (which we show to exist in an overwhelming manner in our data based on statistical tests) while forecasting the entire conditional distribution of stock returns.

[7] The fact that higher oil-price uncertainty tends to have a stronger negative effect on stock returns when stock markets are in their lower conditional quantiles, i.e., during their bearish states, is evident, especially for the short forecast horizons, from Figure A2 for Canada, France, Germany, Switzerland, and the US. For Italy, Japan, and India the coefficients estimated for the lower conditional quantiles are also in general negative, but, as the results for India demonstrate, they are not necessarily larger (in absolute value) than their counterparts in the upper conditional quantiles. This figure plots the full-sample-based quantile response of the average, rather than cumulative, stock returns, due to scale issues in the graphical representation (without compromising on the sign), across the ten countries due to *OIL_UNC* ($\hat{\beta}_i^{(\tau)}$) for the various forecast horizons (h = 1, 3, 6, 9, 12, 18 and 24), covering the entire sample period of 1920:08 to 2021:09.

Our results show that the out-of-sample predictive content of oil-price uncertainty for stock returns is country-specific, as the effect is quite heterogeneous across countries, and, hence, cannot (and should not) be generalized. However, oil-price uncertainty is found to produce significant forecasting gains for stock returns of all of the ten countries considered, though the specificity of the conditional quantiles and forecast horizon varies across the countries. In general, however, the coverage of predictability is associated with normal, bear and, bull-market states, as well as short-, medium-, and long-run horizons. When compared to the common predictive linear-regression approach, we find that the quantile results of forecastability encompasses all ten markets, rather than eight under the former. In addition, under the quantiles-based approach, the forecasting gains are detected at many more horizons (at particular quantiles) compared to the linear predictive regression. Our results, thus, highlight the importance of studying the entire distribution, based on a framework that can account for non-linearity and non-normality, rather than performing just a conditional mean-based analysis, which might be misleading as it is likely to miss important information contained for certain parts of the distribution of stock returns.

In addition, using a regimes-based spillover analysis, we find that the connectedness among the ten international stock markets, though predicted in a different manner by oil-price uncertainty, is stronger in the wake of heightened oil-price uncertainty. This finding, in turn, implies that, in the wake of large unfavourable uncertainty shocks related to the oil market, international portfolio diversification opportunities across stock markets are limited.

Our results further demonstrate that policymakers who use movements in real stock returns following oil-price-uncertainty shocks as a leading indicator for low-frequency macroeconomic variables would be better served by tracing the differently-behaving entire conditional distribution of stock returns, rather than just its conditional mean, when designing

policies aimed at mitigating business-cycle fluctuations and ensuring recovery out of a recession.

In light of the widespread evidence of cross-market volatility spillovers (Tiwari et al., 2018), as part of future research, it is interesting to analyse the second-moment predictability-effect of oil-price uncertainty on stock returns, i.e., on stock-market volatility, based on the historical dataset used in our paper.

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Table 1. Forecasting results

Canada (CA)

		Quantile								
Horizon	Linear	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	0.9980**	1.0150	1.0057	1.0197	1.0074	0.9997	1.0169	1.0160	1.0164	1.144
3	1.0017	0.9998	1.0000	0.9846***	1.0156	0.9980**	0.9917***	1.0285	0.9940***	1.0000
6	0.9980**	0.9621***	0.9626***	1.0012	0.9983**	1.0022	1.0013	0.9873***	0.9945***	0.9265***
9	1.0641	0.9761***	0.9835***	0.9844***	1.0578	1.1103	1.0329	1.0675	1.2132	1.1411
12	1.1553	0.9330***	0.9828***	1.1089	1.0737	1.1749	1.1123	1.2327	1.1309	1.2312
18	1.1320	0.9922***	0.9984**	1.0484	1.0900	1.1163	1.1250	1.2039	1.2192	1.2263
24	1.0694	1.0093	1.0034	1.0020	1.2571	1.1061	1.0691	1.0192	1.0586	1.0462

France (FR)

		Quantile								
Horizon	Linear	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	1.0251	1.1607	1.0457	1.0056	1.0364	1.0031	1.0711	1.2095	1.1462	1.0772
3	1.0209	1.1080	1.0099	1.0365	1.0019	1.0098	1.0517	1.5301	1.3449	1.0926
6	1.0431	1.2209	1.2231	1.1026	1.0036	1.1815	1.4462	1.2086	1.4417	1.0852
9	1.4294	0.8060***	0.9906***	1.1436	1.6721	1.7185	1.6809	1.6962	1.5166	1.2891
12	1.4385	0.8585***	0.9100***	1.5124	1.8152	1.5974	1.5176	1.4567	1.3110	1.2027
18	1.3528	0.9371***	1.1383	1.3144	1.4495	1.3513	1.4295	1.0844	1.2531	1.0528
24	0.9941***	2.0310	1.6327	1.3403	1.0672	0.9785***	0.8190***	0.8782***	0.8927***	0.9258***

Germany (DE)

		Quantile								
Horizon	Linear	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	1.4176	1.1750	0.8222***	0.9614***	0.9707***	1.2425	1.0300	2.4939	1.8366	1.8639
3	1.6517	1.1434	1.1125	1.0936	1.0243	2.5849	2.6628	1.7991	2.1421	1.3476
6	1.3142	3.5451	2.5854	2.2575	0.8455***	1.6159	2.1308	3.3076	1.4995	1.2194
9	0.9971**	1.2140	2.6180	2.6565	4.9158	1.1643	2.8539	1.6979	4.3362	1.2318
12	1.1267	2.1916	1.8270	3.4710	2.0924	1.5209	0.9993*	0.9945***	2.3191	1.2422
18	2.5850	1.5524	1.8803	2.0956	2.5410	1.5859	1.3141	1.1005	0.8732***	0.6903***
24	1.6232	1.7894	1.6333	4.2118	2.6620	1.0992	0.9854***	1.8293	1.1091	0.8259***

India (IN)

		Quantile								
Horizon	Linear	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	1.0857	1.7240	1.2149	1.1133	1.0344	1.0043	1.0015	1.0197	1.0007	1.1186
3	1.1611	1.0341	1.2258	1.1876	1.1786	1.0450	1.0725	1.0465	1.1696	0.9137***
6	1.1925	1.1427	1.2356	1.0328	1.2058	1.0172	1.1481	1.2241	1.0290	0.9332***
9	1.1550	1.0927	1.1351	1.2211	1.3926	1.1182	1.2946	1.1484	0.9901***	1.0171
12	1.2437	1.1970	1.2089	1.3610	1.4850	1.5520	1.2222	1.0406	0.9842***	0.9999
18	1.0908	1.0922	1.2128	1.0453	1.1845	1.2281	1.0832	0.9610***	0.9610***	0.9750***
24	0.9516***	0.8987***	0.9999	0.9831***	0.8714***	0.9564***	0.8902***	0.8005***	0.9850***	1.0321

Italy (IT)

		Quantile								
Horizon	Linear	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	1.0007	1.1022	0.9960***	1.0354	1.0473	1.0337	1.0178	0.9939***	1.0905	1.1920
3	1.0548	0.9328***	0.9686***	0.9758***	0.9883***	1.0203	1.1135	1.2332	1.1777	1.0167
6	1.0347	0.9772***	1.0108	0.9904***	0.9858***	1.0188	1.0202	1.0450	1.3207	1.9168
9	1.1396	0.9962***	0.9226***	0.9622***	0.9786***	1.0112	1.0326	1.4797	3.0196	1.4055
12	1.1953	0.8882***	0.9731***	0.9525***	0.9758***	1.0100	1.0271	3.0478	1.3284	1.4164
18	1.1337	0.9389***	0.9794***	0.9742***	0.9943***	1.0093	1.0906	1.5868	1.6185	1.3491
24	1.0005	1.1307	1.0861	1.0323	1.0197	1.0058	0.9994*	1.1876	1.1627	1.2209

Japan (JP)

		Quantile								
Horizon	Linear	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	1.0048	1.0090	1.0079	1.0331	0.9991*	1.0072	1.0055	1.0336	1.0364	1.2751
3	1.0079	1.0299	1.0359	1.0108	1.0215	0.9988*	1.0031	1.0409	1.1107	1.1536
6	1.0153	1.1587	1.0521	1.0689	1.1444	0.9877***	1.0016	1.0082	1.0010	0.9019***
9	1.1694	1.0982	1.1854	1.2222	1.3247	1.1140	1.0525	0.9935***	1.0427	0.9210***
12	1.1983	0.9589***	1.0424	1.1766	1.3171	1.2843	1.1694	1.1323	1.0128	0.8732***
18	1.2738	1.0021	1.1267	1.1001	1.0518	1.2595	1.2878	1.2550	1.3483	1.1020
24	0.9408***	1.0542	0.9402***	0.9130***	0.9208***	0.9677***	0.9281***	0.9435***	0.9824***	0.9910***

South Africa (ZA)

		Quantile								
Horizon	Linear	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	1.0079	0.9631***	0.9473***	0.9842***	0.9966**	1.0071	0.9962***	0.9973**	0.9929***	1.0229
3	1.0548	0.8283***	0.9522***	0.9965***	1.0026	1.1008	1.2520	1.2392	1.1127	1.0894
6	1.1171	0.9239***	0.9334***	0.9563***	1.0866	1.1281	1.1792	1.1782	1.2355	1.2009
9	1.1175	0.8061***	0.8771***	0.9612***	1.0510	1.1090	1.1599	1.2825	1.3334	1.2622
12	1.0696	0.9107***	0.7970***	0.9908***	1.0138	1.1403	1.0709	1.1330	1.1370	1.0567
18	1.0141	0.9516***	0.9334***	0.9245***	1.0573	1.1359	0.9949***	0.9966**	0.9986**	0.9950***
24	1.1456	1.2272	1.2561	1.3636	1.1097	1.0612	1.0578	1.0058	0.9954***	0.9507***

Switzerland (CH)

		Quantile								
Horizon	Linear	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	1.0204	0.9290***	1.0315	1.0565	1.0209	1.0391	1.0068	0.9830***	1.0074	1.0247
3	1.1437	0.4522***	0.9962***	0.9944***	1.0236	1.0985	1.1754	1.2126	1.1953	1.1661
6	1.1165	0.6385***	1.1369	1.0811	1.0535	1.0582	1.0373	1.0329	0.9838***	0.7994***
9	1.2423	0.8608***	1.4216	1.3856	1.1707	1.0331	1.0175	1.1656	1.0339	1.0212
12	1.2583	0.9800***	1.2718	1.2747	1.1303	1.1448	1.1905	1.3831	1.2275	1.0096
18	1.1429	1.0699	1.0520	1.0831	1.0031	1.0943	0.9883***	1.1353	1.0788	1.3768
24	0.9730***	1.0020	1.0351	0.9687***	0.9831***	0.9793***	1.0097	0.9805***	0.9869***	0.9858***

UK

		Quantile								
Horizon	Linear	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	1.0023	1.0677	1.0541	1.0961	1.0016	1.0048	0.9998	0.9998	1.0236	1.0349
3	1.0013	1.0845	1.0334	1.0453	0.9901***	0.9990*	1.0110	1.0461	1.0398	1.0969
6	0.9921***	1.0180	1.0499	0.9992*	0.9764***	0.9825***	1.0146	1.0363	1.1124	1.2448
9	0.9988*	1.0064	0.9769***	0.9417***	0.9635***	0.9891***	1.0323	1.0542	1.1204	1.3297
12	1.0057	1.0008	0.9627***	0.9707***	0.9640***	0.9785***	1.0160	1.0703	1.1240	1.2243
18	0.9917***	0.9910***	1.0213	0.9817***	0.9783***	0.9989*	0.9917***	0.9918***	0.9985**	1.0980
24	1.0394	1.3147	1.1081	1.0582	1.0345	1.0192	1.0107	1.0186	1.0579	1.0442

US

		Quantile								
Horizon	Linear	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	0.9907***	1.1334	1.1105	0.9950***	1.0052	0.9661***	0.9583***	0.9518***	0.9434***	0.9894***
3	0.9817***	1.1144	1.1073	1.0307	0.9946***	0.9811***	0.9949***	0.8965***	0.8889***	0.8665***
6	0.9789***	1.1636	1.1357	1.0287	1.0104	0.9926***	0.9565***	0.9049***	0.9341***	0.7939***
9	1.0052	1.2372	1.1513	1.0293	1.0279	1.0864	1.1258	1.1438	1.2257	1.0315
12	1.0830	1.0107	1.0364	0.9209***	1.5974	1.3401	1.0593	1.0440	1.0660	1.2161
18	1.1733	0.9291***	0.9598***	1.1178	1.3775	1.2569	1.1599	1.0849	1.1491	1.1675
24	1.4589	1.2233	1.3722	1.3257	1.2879	1.8856	1.3823	1.3940	1.3036	1.3293

Note: In-sample: 1920:08-1925:07; Out-of-sample: 1925:08-2021:09; ***, ** and * indicates significance for the *MSE-F* statistic of McCracken (2007) at 1%, 5% and 10% levels respectively, whilst τ specifies the quantile; $MSFE_{UR}$ / $MSFE_{R}$ signifies the Mean Square Forecast Error (RMSFE) ratio of the corresponding linear ($r_{t+1} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{t+1}$) or quantile regression ($r_{t+1} = \alpha_i^{(\tau)} + \beta_i^{(\tau)} x_{i,t} + \varepsilon_{t+1}$) models over the one generated by the benchmarks ($r_{t+1} = \alpha_i + \varepsilon_{t+1}$or $r_{t+1} = \alpha_i^{(\tau)} + \varepsilon_{t+1}, respectively$).

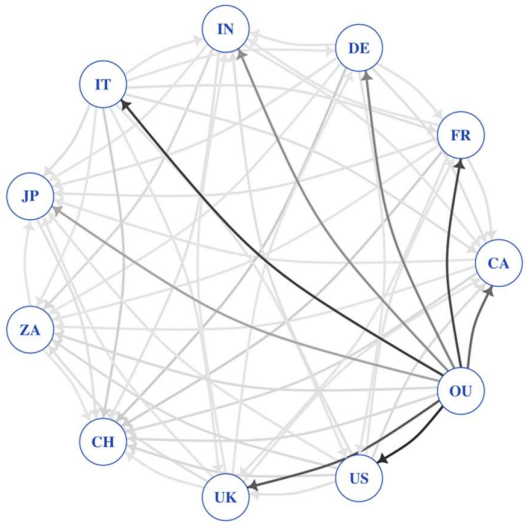
Table 2. Regime dependent connectedness based on STVAR model

	Lower regime											
	CA	FR	DE	IN	IT	JP	ZA	CH	UK	US	OIL_UNC	From
CA	14.55	3.86	2.93	2.88	3.07	1.18	0.8	3.68	0.44	7.31	59.29	85.45
FR	1.94	14.82	2.53	0.27	3.39	1.04	0.05	2.49	0.21	1.22	72.04	85.18
DE	0.91	1.51	44.01	0.15	1.64	0.98	0.02	1.69	0.14	0.75	48.2	55.99
IN	2.39	0.41	0.4	40.59	0.38	0.08	6.1	0.78	3.11	4.4	41.34	59.41
IT	0.71	1.37	1.41	0.11	17.34	0.77	0.01	0.92	0.12	0.65	76.58	82.66
JP	1.45	2.62	1.89	0.13	4.41	55.5	0.04	1.97	0.58	0.91	30.49	44.5
ZA	1.5	0.11	0.09	11.99	0.03	0.04	66.15	0.4	7.16	6.97	5.55	33.85
CH	9.36	13.39	14.63	2.41	11.08	4.02	0.5	31.03	0.6	7.51	5.46	68.97
UK	0.17	0.47	0.13	3.04	0.53	0.51	4.73	0.06	22.67	2.42	65.28	77.33
US	2.95	0.97	0.87	2.29	1.22	0.33	1.86	1.1	1.18	4.86	82.37	95.14
OU	0.02	0	0	0.01	0.02	0.08	0	0.01	0	0	99.86	0.14
To	21.41	24.72	24.88	23.27	25.78	9.03	14.13	13.1	13.54	32.14	486.62	**62.6**
Net	-64.04	-60.46	-31.11	-36.13	-56.88	-35.47	-19.72	-55.86	-63.79	-63	486.47	
	Upper regime											
	CA	FR	DE	IN	IT	JP	ZA	CH	UK	US	OIL_UNC	From
CA	1.85	0.51	0.36	0.35	0.44	0.16	0.12	0.45	0.11	0.87	94.79	98.15
FR	0.43	3.28	0.5	0.06	0.82	0.28	0	0.56	0.1	0.4	93.56	96.72
DE	0.31	0.5	15.4	0.17	0.61	0.15	0.02	0.57	0.04	0.23	82.01	84.6
IN	0.41	0.1	0.08	7.97	0.14	0.02	1.09	0.15	0.46	0.76	88.84	92.03
IT	0.24	0.48	0.48	0.11	5.59	0.31	0	0.31	0.02	0.24	92.22	94.41
JP	0.12	0.25	0.3	0.04	0.37	4.83	0	0.19	0.04	0.09	93.76	95.17
ZA	0.78	0.09	0.06	6.08	0.02	0.02	34.2	0.28	3.59	3.41	51.46	65.8
CH	0.26	0.38	0.37	0.06	0.32	0.13	0.01	0.82	0.02	0.24	97.37	99.18
UK	0.01	0.08	0.03	0.53	0.07	0.07	0.75	0.01	4.13	0.53	93.8	95.87
US	1.57	0.57	0.48	1.24	0.76	0.16	1.03	0.61	0.61	2.61	90.37	97.39
OU	0	0	0	0	0	0	0	0	0	0	100	0
To	4.13	2.97	2.63	8.63	3.56	1.3	3.02	3.14	4.99	6.76	878.2	**83.58**
Net	-94.02	-93.74	-81.97	-83.4	-90.86	-93.87	-62.78	-96.05	-90.88	-90.63	878.2	

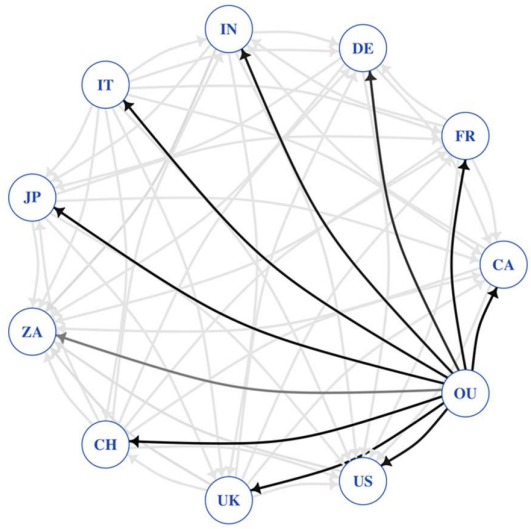
Note: CA: Canada; FR: France; DE: Germany; IN: India; IT: Italy; JP: Japan; ZA: South Africa; CH: Switzerland; UK: the United Kingdom; US: the United States. The table reports the regime dependent connectedness measures computed in similar manner to Diebold and Yilmaz (2012). The lag order of the STVAR models is 1 which is selected by the Bayesian information criterion (BIC) in a linear VAR model. The threshold variable is the oil uncertainty. Lower regime corresponds to regime periods below the estimated threshold (low uncertainty) while upper regime corresponds to periods above the threshold (high uncertainty). The STVAR smoothness and threshold parameter estimates are 44.876 and 59.709, respectively. Boldface denotes overall spillover index.

Figure 1. Connectedness based on the STVAR model

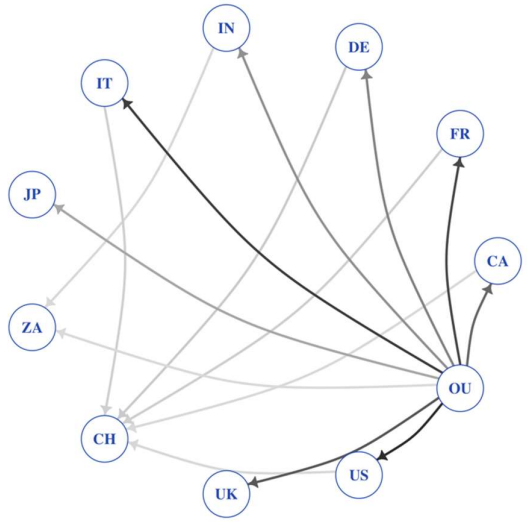
(a) Net connectedness without thresholding in the lower regime



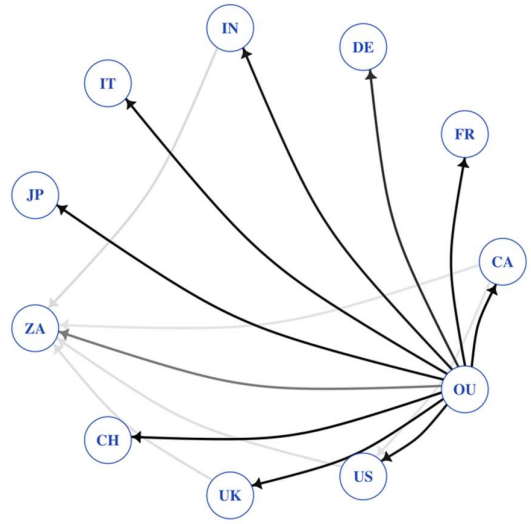
(b) Net connectedness without thresholding in the upper regime



(c) Net connectedness with thresholding in the lower regime



(d) Net connectedness with thresholding in the upper regime



Note: See Notes to Table 2. Net connectedness is based on the pairwise net spillovers obtained the STVAR model estimates reported in Table 2. Thresholding sets values below the 75-th percentile of the spillover to zero. Darker color intensity indicates stronger links.

APPENDIX:
Table A1. Summary statistics

	Canada	France	Germany	India	Italy	Japan
Statistic	CA	FR	DE	IN	IT	JP
Mean	0.206	0.394	0.187	-0.106	0.319	0.358
S.D.	4.592	5.503	8.073	6.253	7.058	6.034
Min	-32.011	-28.017	-147.279	-64.254	-30.782	-26.279
Max	20.589	24.256	68.264	27.690	46.811	51.287
Skewness	-1.106	-0.253	-4.717	-1.119	0.760	0.580
Kurtosis	5.618	1.822	100.959	13.170	5.591	7.124
JB	1852.385***	182.403***	521844.876***	9063.431***	1706.435***	2647.451***

	South Africa	Switzerland	UK	US	Oil Uncertainty (*OIL_UNC*)
Statistic	ZA	CH	UK	US	OU
Mean	0.040	0.159	0.024	0.310	70.975
S.D.	5.954	4.374	5.165	4.406	165.337
Min	-31.650	-28.479	-34.430	-30.753	1.008
Max	27.201	28.778	36.116	41.484	2536.770
Skewness	-0.048	-0.510	-0.178	-0.465	7.922
Kurtosis	3.156	4.988	6.059	11.969	89.223
JB	507.507***	1317.739***	1872.398***	7319.968***	416781.610***

Note: Table reports the descriptive statistics on the stock log-returns of Canada (CA), France (FR), Germany (DE), India (IN), Italy (IT), Japan (JP), South Africa (ZA), Switzerland (CH), the UK, the US, and the oil price uncertainty based on the GARCH(1,1,)-based volatility estimate of the WTI oil log-returns series. Along with the mean, standard deviation (SD), minimum and maximum values, skewness, and excess kurtosis, the table includes the Jarque-Bera test of normality (JB).

Table A2. BDS test results

Canada (CA)

			m		
Horizon	2	3	4	5	6
1	5.4804***	7.2432***	7.7305***	8.0552***	8.3996***
3	30.0470***	29.8887***	30.0940***	30.5043***	31.2106***
6	48.8757***	49.5146***	50.2101***	51.8332***	54.7206***
9	59.7664***	61.5225***	63.5063***	66.8864***	71.8290***
12	66.6430***	69.3991***	72.3594***	76.7925***	83.0177***
18	73.4330***	77.3927***	81.6248***	87.7516***	96.1108***
24	73.9455***	77.8864***	82.5771***	89.3594***	98.4716***

France (FR)

			m		
Horizon	2	3	4	5	6
1	6.3620***	7.2471***	7.9322***	8.4771***	9.2419***
3	32.0595***	31.0787***	31.0264***	31.4570***	32.2572***
6	50.4667***	50.4568***	50.7707***	52.1863***	54.5124***
9	60.2360***	62.0011***	63.7013***	66.6309***	70.9955***
12	71.1355***	74.1394***	77.2470***	81.9037***	88.3707***
18	78.0588***	82.0287***	86.4896***	92.8287***	101.4192***
24	84.1488***	89.0199***	94.7484***	102.8983***	113.8628***

Germany (DE)

			m		
Horizon	2	3	4	5	6
1	-0.0304	-0.0408	-0.0489	-0.0558	-0.0619
3	22.1413***	19.8431***	17.8224***	16.2627***	15.0398***
6	49.1776***	49.8417***	50.7371***	52.9877***	56.5639***
9	57.4173***	59.4958***	61.9414***	65.7028***	70.9413***
12	64.2860***	67.0138***	70.1761***	75.0193***	81.7098***
18	65.8235***	69.5390***	73.6751***	79.6903***	87.8614***
24	68.1973***	72.3469***	77.2291***	84.2390***	93.6809***

India (IN)

			m		
Horizon	2	3	4	5	6
1	6.6610***	7.8605***	8.7403***	9.7294***	10.8895***
3	34.2447***	33.4717***	33.1863***	33.8146***	35.2266***
6	55.9590***	56.5965***	57.3946***	59.3295***	62.5465***
9	68.4950***	70.3921***	72.5318***	75.9896***	81.2207***
12	82.4923***	85.7183***	89.1765***	94.5480***	102.2504***
18	100.5006***	105.5870***	111.3451***	119.6967***	130.9977***
24	101.6299***	107.1692***	113.8164***	123.5633***	136.7903***

Italy (IT)

	m				
Horizon	2	3	4	5	6
1	8.1219***	9.9043***	11.8050***	12.9516***	14.0496***
3	31.1155***	31.2116***	32.0832***	33.2771***	34.8462***
6	45.0681***	46.1790***	47.1035***	49.0987***	52.1795***
9	52.6023***	54.2944***	56.5492***	60.0800***	64.952***
12	58.6007***	61.2763***	64.2609***	68.9322***	75.3187***
18	65.6667***	68.8835***	72.6163***	78.1481***	85.6733***
24	72.3672***	76.4420***	81.2412***	88.1203***	97.4060***

Japan (JP)

	m				
Horizon	2	3	4	5	6
1	7.7895***	10.5237***	12.3909***	13.5504***	14.7601***
3	32.6978***	33.0664***	33.4913***	34.4981***	36.0140***
6	46.1696***	47.9324***	49.0691***	51.0530***	54.0522***
9	56.6341***	59.0716***	61.5812***	65.3488***	70.3983***
12	64.5106***	67.6304***	71.1540***	76.2769***	83.1049***
18	70.9028***	75.1158***	79.5581***	85.7982***	94.2258***
24	72.6994***	77.0989***	82.1197***	89.3549***	99.0218***

South Africa (ZA)

	m				
Horizon	2	3	4	5	6
1	8.2964***	9.4845***	10.8520***	11.6503***	12.7213***
3	34.1471***	33.4270***	33.7088***	34.5045***	35.8966***
6	57.9810***	58.3660***	58.8450***	60.6053***	63.7685***
9	72.9328***	75.2876***	77.8432***	81.9912***	87.8248***
12	80.7393***	84.4037***	88.4145***	94.6587***	103.1594***
18	83.4895***	88.1933***	93.5529***	101.3645***	111.9483***
24	92.3261***	97.6548***	103.8140***	112.8047***	125.0195***

Switzerland (CH)

	m				
Horizon	2	3	4	5	6
1	7.4940***	7.8755***	9.0694***	9.7816***	10.7581***
3	31.9384***	30.7749***	30.6713***	31.4211***	32.7586***
6	49.7216***	50.8735***	52.0055***	54.1263***	57.3040***
9	63.0756***	65.3880***	67.7258***	71.4613***	76.8146***
12	71.2159***	74.5311***	78.1453***	83.4362***	90.5305***
18	83.8940***	88.6358***	94.0200***	101.6712***	111.9015***
24	85.7254***	90.8166***	96.7568***	105.1647***	116.4791***

UK

			m		
Horizon	2	3	4	5	6
1	7.3849***	9.5479***	10.6744***	11.9226***	12.6929***
3	26.9010***	27.2498***	27.9282***	28.9153***	30.2618***
6	41.1060***	41.7911***	42.3479***	43.6310***	45.9965***
9	48.1450***	49.6972***	51.4142***	54.0192***	57.7359***
12	52.6877***	54.8292***	57.1575***	60.8198***	65.7464***
18	62.3997***	65.7829***	69.4332***	74.7400***	81.8649***
24	65.9381***	69.7089***	73.9110***	79.8362***	87.8560***

US

			m		
Horizon	2	3	4	5	6
1	7.2639***	8.4353***	9.4870***	10.3174***	11.2059***
3	33.4457***	33.8675***	34.6486***	35.9221***	37.9822***
6	50.0905***	50.9738***	52.1340***	54.4882***	58.1975***
9	58.4171***	60.6130***	63.3531***	67.6082***	73.4821***
12	65.5209***	68.5206***	71.9698***	77.0623***	84.1272***
18	69.3140***	72.9984***	77.4758***	83.9991***	92.7723***
24	71.3134***	75.2479***	80.0222***	86.9867***	96.3795***

Note: *m* stands for the number of (embedded) dimension which embed the time series into *m*-dimensional vectors, by taking each m successive points in the series; Test applied to residuals of Eq. (1): $r_{t+1} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{t+1}$; entries correspond to the null hypothesis of *i.i.d.* residuals based on the *z*-statistic of the BDS (Brock et al., 1996) test.

Table A3. Multiple structural break test results

Canada (CA)

Horizon	Dates
1	1940M12, 1956M08, 1975M01
3	
6	
9	1937M07, 1952M11, 1967M11, 1982M11, 2000M11
12	1937M09, 1957M02, 1975M08, 1990M10, 2006M09
18	1937M08, 1957M02, 1975M11, 1990M10, 2006M11
24	1937M09, 1952M07, 1967M05, 1983M08, 2001M06

France (FR)

Horizon	Dates
1	1939M10, 1962M05
3	1939M11, 1962M06
6	1940M02, 1962M06
9	1940M04, 1960M06, 1975M06, 1990M06, 2006M10
12	1940M06, 1960M09, 1975M09, 1990M09, 2006M10
18	1940M12, 1960M12, 1975M11, 1990M10, 2006M11
24	1940M06, 1961M02, 1975M12, 1990M10, 2006M12

Germany (DE)

Horizon	Dates
1	1935M10, 1950M12, 1966M03, 1982M09, 2000M03
3	1935M11, 1951M01, 1966M04, 1982M09, 2000M05
6	1936M02, 1951M03, 1966M04, 1982M11, 2000M06
9	1936M04, 1951M04, 1966M04, 1982M12, 2000M09
12	1936M07, 1951M07, 1966M07, 1982M12, 2000M11
18	1950M01, 1964M12, 1983M02, 2001M02
24	1950M07, 1965M05, 1982M12, 2000M11

India (IN)

Horizon	Dates
1	1940M12, 1956M04, 1976M07, 1991M08, 2006M09
3	1940M12, 1956M05, 1976M07, 1991M08, 2006M09
6	1941M03, 1956M08, 1976M07, 1991M08, 2006M09
9	1941M06, 1956M09, 1975M10, 1990M10, 2005M10
12	1947M07, 1968M03, 1987M05, 2002M06
18	1948M01, 1969M01, 1986M04, 2002M04
24	1948M05, 1977M05, 1995M09

Italy (IT)

Horizon	Dates
1	
3	
6	1939M06, 1961M07, 1978M05
9	1939M06, 1960M10, 1975M10, 1990M10, 2006M10
12	1939M07, 1960M10, 1975M10, 1990M10, 2006M10

18	1939M10, 1960M12, 1975M11, 1990M10, 2006M11
24	1939M11, 1962M06, 1979M02, 2001M02

Japan (JP)

Horizon	Dates
1	
3	
6	1944M12, 1960M01, 1975M02, 1990M03, 2005M04
9	1945M04, 1960M04, 1975M04, 1990M04, 2005M05
12	1945M07, 1960M07, 1975M07, 1990M07, 2005M07
18	1947M12, 1962M11, 1989M10, 2004M09
24	1948M01, 1962M11, 1990M02, 2004M12

South Africa (ZA)

Horizon	Dates
1	1940M06, 1974M02
3	1941M05, 1956M09, 1974M04, 1991M07, 2006M09
6	1941M05, 1961M09, 1981M01, 2000M10
9	1941M05, 1961M11, 1981M02, 2001M01
12	1947M05, 1962M05, 1981M05, 2001M03
18	1947M10, 1962M09, 1981M11, 2001M02
24	1948M06, 1963M04, 1982M02, 2000M12

Switzerland (CH)

Horizon	Dates
1	1945M04, 1962M03, 1982M08, 1998M08
3	1945M05, 1962M04, 1982M09, 1998M08
6	1945M08, 1962M05, 1982M11, 1998M08
9	1945M09, 1962M05, 1982M11, 1998M09
12	1939M01, 1962M05, 1982M12, 2001M03
18	1939M06, 1962M07, 1983M02, 1999M07
24	1939M06, 1962M10, 1983M07, 2000M01

UK

Horizon	Dates
1	1941M08, 1956M12, 1974M04, 1990M12, 2006M09
3	1941M06, 1967M05, 1982M09
6	1941M10, 1957M01, 1975M01, 1991M04, 2006M09
9	1941M10, 1956M12, 1975M01, 1991M04, 2006M10
12	1941M07, 1957M01, 1975M01, 1990M01, 2006M10
18	1941M10, 1957M03, 1975M04, 1990M03, 2006M11
24	1941M09, 1957M03, 1975M01, 1989M11, 2006M12

US

Horizon	Dates
1	
3	

6	1937M04, 1952M05, 1967M08, 1982M09, 1999M09
9	1937M05, 1952M07, 1967M11, 1982M11, 2000M08
12	1937M06, 1952M06, 1968M01, 1983M01, 2000M04
18	1937M05, 1952M04, 1967M03, 1983M02, 2000M09
24	1937M09, 1952M07, 1967M05, 1983M04, 2000M11

Note: Test applied to Eq. (1): $r_{t+1} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{t+1}$; entries correspond to the break dates based on Bai and Perron (2003) tests of multiple structural breaks.

Table A4. Alternative forecasting results

Canada (CA)

		Quantile								
Horizon	Linear	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	1.0096	1.0539	1.0207	1.0063	1.0056	1.0692	1.0225	1.0565	1.0541	1.0681
3	1.1653	0.9834***	1.0260	1.0137	1.1749	1.1579	1.3767	1.1520	1.0041	1.1533
6	1.0695	3.6724	2.8853	1.5703	1.0828	1.0428	0.9909***	1.0160	1.7642	2.5774
9	1.0097	1.0775	1.0009	1.0102	1.0289	1.0012	1.0055	1.0082	1.0198	1.1721
12	1.0426	1.1246	1.0181	0.9767***	1.0041	0.9960***	1.0777	1.0577	1.0481	1.0280
18	1.0415	0.9319***	1.0219	0.9984**	1.0093	1.0224	1.0306	1.0739	0.9909***	0.9967**
24	1.1414	1.1748	1.0304	1.2822	1.0970	1.0810	1.0539	1.0424	0.9874***	0.9849***

France (FR)

		Quantile								
Horizon	Linear	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	1.0313	1.0527	1.0000	1.0215	1.0231	1.1059	1.0470	1.0838	1.1175	1.1217
3	1.1494	0.9469***	0.9420***	1.1186	1.1266	1.1617	1.1589	1.0852	1.1215	1.0157
6	1.0095	1.0188	0.9864***	1.0475	1.0057	1.0044	1.0184	0.9977**	0.9696***	1.0002
9	1.0015	1.0973	1.0783	1.0000	0.9929***	0.9913***	1.0098	0.9977**	0.9986**	1.1446
12	0.9937***	1.0030	0.9432***	0.9674***	1.0113	1.0188	0.9883***	0.9917***	1.0205	1.0648
18	1.0137	0.9867***	1.1046	1.0585	1.0279	1.0175	1.0282	0.9880***	1.1046	0.9785***
24	1.3594	1.1084	1.0417	1.5507	1.3332	1.3228	1.3951	1.4304	1.2986	2.5698

Germany (DE)

		Quantile								
Horizon	Linear	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	1.0279	1.1018	0.9898***	1.0360	1.0204	1.0448	1.1372	1.0048	1.1026	1.0208
3	1.1151	0.9379***	1.0549	1.2953	1.1239	1.1144	1.0876	1.0256	1.0308	1.0686
6	1.0230	1.0046	0.9894***	1.0064	1.0024	1.0043	1.0321	1.0120	1.0740	1.0010
9	1.0030	1.2079	0.9989*	1.0230	1.0217	0.9938***	0.9912***	0.9995	1.0267	0.9872***
12	0.9980**	1.0389	0.9968**	1.0012	0.9947***	0.9985**	0.9969**	1.0231	0.9805***	1.0071
18	1.0313	0.9988*	1.0337	1.0673	1.0675	1.0283	1.0253	1.0513	0.9915***	0.9369***
24	1.9997	1.2953	1.3754	1.6164	1.7809	2.1678	2.3916	2.3820	3.2277	4.1536

India (IN)

		Quantile								
Horizon	Linear	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	1.0978	1.4814	1.0274	1.2574	1.1813	1.1473	1.1468	1.0286	1.1446	1.0188
3	1.0085	1.0727	1.0415	1.4281	1.1178	1.0832	0.9824***	0.9711***	1.0006	1.0187
6	1.0248	1.0924	0.9995	1.0007	1.0071	1.0155	1.0914	1.0631	1.0370	0.9494***
9	1.0184	1.0396	1.0065	1.0293	1.0306	0.9973**	0.9981**	0.9995	0.9757***	1.1052
12	0.9998	1.0349	0.9828***	0.9998	1.0011	1.0048	1.0216	0.9920***	0.9639***	1.0069
18	1.0422	0.9695***	0.9801***	1.0793	1.1084	1.0888	1.1171	1.0380	0.9846***	1.0141
24	1.0024	1.0503	0.9541***	1.0345	1.0017	1.0018	1.0207	1.0009	1.0319	1.0166

Italy (IT)

		Quantile								
Horizon	Linear	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	1.1823	0.7720***	1.1620	1.5118	1.4267	1.2264	1.1427	1.1004	1.1092	1.0123
3	1.1822	1.0281	1.7459	1.4004	1.3863	1.0002	1.0119	0.9681***	1.0874	1.0138
6	1.0074	0.8750***	1.0080	1.0002	1.0014	0.9872***	1.0717	1.0194	1.0022	1.0442
9	1.2124	1.0220	1.1897	1.1015	1.0460	1.0197	1.1358	1.4979	1.2484	1.3853
12	1.0000	1.0521	1.0373	0.9943***	1.0061	0.9979**	1.0209	1.0349	1.0578	1.1765
18	1.0291	1.0006	1.0080	1.0531	1.0765	1.1013	1.0739	1.0585	1.0108	0.9812***
24	1.0053	1.0635	1.0201	1.0394	1.0173	1.0704	1.0097	0.9958***	1.0163	1.0753

Japan (JP)

		Quantile								
Horizon	Linear	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	1.2420	0.9940***	1.2484	1.7484	1.6886	1.3154	1.1184	1.0560	1.0853	1.0603
3	1.2625	1.7774	1.7937	1.0878	1.0151	1.0109	1.0547	1.1246	1.0573	1.1131
6	1.0223	0.9873***	1.0180	1.0746	1.0076	1.0391	1.0806	1.0392	0.9947***	1.0003
9	1.0012	1.0090	1.0027	1.0031	1.0031	1.0054	0.9999	1.0020	1.0002	1.0206
12	0.9974**	1.0620	1.0324	0.9806***	1.0010	0.9980**	1.0126	1.0178	1.0751	1.1429
18	1.0002	1.5033	1.0417	1.0012	1.0367	1.1547	1.0448	0.9856***	0.9976**	1.0058
24	1.0025	1.1077	1.0006	1.0076	1.1255	1.0761	1.0774	1.0424	1.0013	0.9898***

South Africa (ZA)

		Quantile								
Horizon	Linear	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	1.4650	0.9945***	1.8966	2.1014	1.9733	1.8073	1.9312	1.2950	1.0204	0.9817***
3	1.0708	1.4051	1.3542	1.1024	0.9813***	1.0104	1.0200	1.0921	1.0107	1.0261
6	0.9947***	1.0304	1.0222	0.9977**	1.0135	0.9369***	0.9627***	1.0376	1.0192	1.0136
9	0.9999	1.0205	1.0358	0.9965***	1.0090	0.9984**	1.0001	1.0009	0.9941***	1.0138
12	1.0070	1.0895	0.9975**	0.9957***	0.9749***	0.9918***	1.0050	0.9994*	1.0011	0.9736***
18	1.0216	1.0691	1.1364	1.0466	1.0634	1.0373	1.0168	1.0039	0.9895***	1.0167
24	1.0402	1.1938	1.0024	1.0669	1.1141	1.1288	1.1311	1.1342	0.9889***	1.0083

Switzerland (CH)

		Quantile								
Horizon	Linear	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	1.0279	1.0496	1.0018	1.0119	1.0090	0.9998	1.0692	1.1040	1.1118	1.1047
3	0.9998	1.2222	1.1021	1.0053	1.0216	1.1108	1.0138	0.8667***	1.0533	1.0154
6	1.0565	0.9798***	1.0370	1.0100	0.9812***	1.1639	1.1867	1.0328	1.0160	1.0183
9	1.0301	1.1459	1.0247	1.0025	1.0043	1.0047	1.0113	1.0100	1.0238	1.0247
12	1.0419	0.9803***	0.9976**	1.0122	1.0058	1.1001	1.0572	1.0242	1.0173	0.9930***
18	1.0600	1.0691	1.0739	1.1491	1.0879	1.0784	1.0828	1.0381	0.9783***	1.0375
24	1.0990	0.9874***	0.9947***	1.1388	1.2852	1.2089	1.1239	1.0596	1.0010	1.1398

UK

		Quantile								
Horizon	Linear	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	1.0434	1.0109	1.0136	1.0100	0.9996	1.0531	1.0868	1.2331	1.1611	1.0767
3	1.0323	1.4793	1.0448	1.0267	1.0649	1.0963	1.0343	0.9485***	0.9670***	0.9797***
6	1.0012	1.2523	1.0781	1.0078	1.0069	1.0031	1.0022	0.9990*	1.0072	1.1252
9	1.0847	1.0446	1.0154	1.0109	1.0584	1.0510	1.0718	1.0722	1.0875	1.0844
12	1.3548	1.2745	1.2623	1.3162	1.3016	1.2363	1.2374	1.1294	1.0468	1.0564
18	1.0766	1.1655	1.0600	1.0944	1.1366	1.1212	1.0326	1.0043	1.0045	1.0186
24	1.1771	1.0165	1.4577	1.2638	1.1698	1.1418	1.2222	1.1263	1.0788	0.9917***

US

		Quantile								
Horizon	Linear	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	1.0497	1.0348	1.0002	0.9872***	0.9995	1.1256	1.0973	1.1177	1.1432	1.0528
3	1.3280	0.9840***	1.3684	1.0353	1.0276	1.0337	1.0000	2.7862	1.4646	1.3231
6	1.0004	1.0385	0.9756***	0.9718***	0.9942***	1.0033	1.0291	1.0555	1.0440	1.0169
9	1.0755	0.9941***	0.9895***	0.9877***	1.0202	1.0466	1.0866	1.0581	1.0790	1.0206
12	1.0067	1.0155	1.0299	1.0278	1.0109	1.0037	0.9989*	0.9788***	1.0072	1.0008
18	1.0942	1.1269	1.1496	1.1291	1.1904	1.0899	1.0626	1.0094	1.0057	1.0084
24	1.4691	1.8355	1.9966	1.5954	1.4648	1.3589	1.2509	1.2500	1.2216	1.0107

Note: See Note to Table 1. In-sample: 1920:08-1930:07; Out-of-sample: 1930:08-2021:09.

Table A5. Regime dependent connectedness based on TVAR model

	Lower regime											
	CA	FR	DE	IN	IT	JP	ZA	CH	UK	US	*OIL_UNC*	From
CA	26.75	7.13	5.38	5.24	5.59	2.09	1.48	6.80	0.79	13.46	25.29	73.25
FR	3.28	24.97	4.25	0.44	5.70	1.71	0.09	4.20	0.34	2.06	52.95	75.03
DE	1.49	2.48	71.54	0.24	2.63	1.49	0.04	2.75	0.23	1.24	15.88	28.46
IN	2.16	0.37	0.35	36.20	0.33	0.08	5.44	0.68	2.73	3.90	47.76	63.80
IT	0.96	1.88	1.95	0.14	23.71	1.04	0.01	1.26	0.16	0.89	67.98	76.29
JP	1.84	3.31	2.41	0.16	5.59	69.87	0.06	2.48	0.72	1.15	12.41	30.13
ZA	1.63	0.11	0.09	11.89	0.04	0.04	65.67	0.42	7.13	6.96	6.03	34.33
CH	6.16	8.74	9.54	1.54	7.16	2.63	0.33	20.06	0.38	4.88	38.59	79.94
UK	0.15	0.45	0.13	2.85	0.52	0.48	4.43	0.06	21.22	2.26	67.45	78.78
US	4.64	1.53	1.36	3.52	1.90	0.47	2.90	1.71	1.83	7.59	72.55	92.41
OU	0.01	0.01	0.01	0.01	0.03	0.08	0.01	0.00	0.00	0.00	99.85	0.15
To	22.33	26.00	25.49	26.02	29.49	10.10	14.78	20.37	14.31	36.80	406.88	**57.51**
Net	-50.91	-49.03	-2.97	-37.78	-46.80	-20.03	-19.55	-59.57	-64.47	-55.61	406.73	
	Upper regime											
	CA	FR	DE	IN	IT	JP	ZA	CH	UK	US	*OIL_UNC*	From
CA	2.20	0.61	0.43	0.40	0.51	0.19	0.13	0.55	0.13	1.05	93.80	97.80
FR	0.48	3.58	0.55	0.07	0.89	0.31	0.01	0.62	0.10	0.45	92.96	96.42
DE	0.37	0.61	18.72	0.20	0.73	0.18	0.02	0.69	0.04	0.28	78.16	81.28
IN	0.37	0.09	0.07	7.21	0.12	0.02	0.99	0.14	0.42	0.69	89.88	92.79
IT	0.25	0.51	0.47	0.11	6.04	0.32	0.00	0.32	0.03	0.26	91.70	93.96
JP	0.16	0.33	0.36	0.04	0.49	6.40	0.00	0.25	0.05	0.11	91.80	93.60
ZA	0.57	0.09	0.04	4.87	0.02	0.03	27.08	0.20	2.88	2.70	61.52	72.92
CH	0.31	0.44	0.44	0.07	0.38	0.15	0.02	0.99	0.03	0.29	96.88	99.01
UK	0.01	0.09	0.04	0.60	0.08	0.08	0.82	0.01	4.53	0.54	93.20	95.47
US	2.03	0.76	0.62	1.59	0.98	0.20	1.34	0.79	0.79	3.40	87.51	96.60
OU	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00
To	4.55	3.53	3.01	7.95	4.21	1.46	3.33	3.55	4.47	6.36	877.42	**83.62**
Net	-93.25	-92.89	-78.27	-84.83	-89.75	-92.14	-69.58	-95.46	-91.00	-90.24	877.42	

Note: See Note to Table A1. The table reports the regime dependent connectedness measures computed in similar manner to Diebold and Yilmaz (2012). The lag order of the TVAR models is 1 which is selected by the Bayesian information criterion (BIC) in a linear VAR model. The threshold variable is the oil uncertainty. Lower regime corresponds to regime periods below the estimated threshold (low uncertainty) while upper regime corresponds to periods above the threshold (high uncertainty). The TVAR threshold parameter estimate is 55.961. Boldface denotes overall spillover index.

Table A6. Regime dependent connectedness based on MSVAR model

	Regime 1											
	CA	FR	DE	IN	IT	JP	ZA	CH	UK	US	*OIL_UNC*	From
CA	83.24	0.21	0.04	0.07	0.21	0.01	0.64	1.47	0.18	8.58	5.33	16.76
FR	1.61	58.10	0.13	0.05	0.90	0.02	0.12	9.52	0.22	0.57	28.76	41.90
DE	1.16	0.00	55.40	0.09	2.67	0.18	0.54	0.59	0.62	1.99	36.77	44.60
IN	0.05	0.03	0.80	35.89	0.04	0.01	0.00	0.65	0.22	0.18	62.13	64.11
IT	1.19	0.00	0.13	0.01	88.78	2.07	0.67	2.13	0.01	0.22	4.78	11.22
JP	0.20	0.07	0.10	0.71	0.91	50.52	0.18	1.26	0.89	4.86	40.30	49.48
ZA	0.14	0.06	0.03	0.17	0.02	0.08	31.56	0.00	0.24	0.14	67.56	68.44
CH	1.80	0.03	0.02	0.10	0.12	0.00	0.20	94.26	0.07	0.82	2.58	5.74
UK	7.07	0.02	0.38	4.45	0.49	0.26	0.24	0.16	55.44	10.80	20.68	44.56
US	5.68	0.02	0.01	0.28	0.02	0.03	0.03	2.85	1.02	37.80	52.25	62.20
OU	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	99.99	0.01
To	18.90	0.45	1.65	5.93	5.40	2.67	2.62	18.62	3.47	28.18	321.13	**37.18**
Net	2.15	-41.45	-42.95	-58.18	-5.82	-46.81	-65.82	12.88	-41.09	-34.02	321.12	
	Regime 2											
	CA	FR	DE	IN	IT	JP	ZA	CH	UK	US	*OIL_UNC*	From
CA	18.84	0.03	0.03	0.13	0.01	0.06	1.62	2.49	0.01	0.16	76.63	81.16
FR	0.92	9.37	0.05	0.01	0.67	0.21	0.97	0.17	0.00	0.48	87.16	90.63
DE	1.14	0.04	23.32	0.52	0.01	0.55	3.17	9.05	1.48	3.28	57.43	76.68
IN	5.83	0.64	0.06	49.80	0.14	0.52	7.67	0.17	3.49	14.80	16.89	50.20
IT	28.46	4.85	2.62	0.24	26.22	10.02	0.62	0.31	1.62	10.91	14.13	73.78
JP	3.87	0.56	4.10	0.38	0.35	23.42	1.30	4.52	0.21	31.14	30.15	76.58
ZA	0.34	0.40	0.00	0.56	0.02	0.23	13.32	0.76	1.62	2.23	80.51	86.68
CH	2.03	0.27	0.07	0.03	0.06	0.02	6.65	63.14	0.31	2.50	24.91	36.86
UK	19.76	2.31	0.02	0.31	0.44	0.05	4.82	6.48	34.87	6.61	24.34	65.13
US	6.10	0.03	0.01	0.11	0.01	0.52	2.11	4.74	1.10	23.65	61.62	76.35
OU	0.04	0.01	0.00	0.05	0.02	0.02	0.02	0.01	0.11	0.06	99.66	0.34
To	68.50	9.13	6.97	2.35	1.72	12.19	28.94	28.69	9.95	72.18	473.76	**64.94**
Net	-12.66	-81.50	-69.71	-47.85	-72.06	-64.39	-57.74	-8.17	-55.18	-4.17	473.42	

Note: See Notes to Table A1. The table reports the regime dependent connectedness measures computed in similar manner to Diebold and Yilmaz (2012). The lag order of the MSVAR models is 1 which is selected by the Bayesian information criterion (BIC) in a linear VAR model. Regime 1 corresponds to lower variance (low uncertainty) estimates while upper Regime 2 corresponds to higher variance (high uncertainty) estimates. Boldface denotes overall spillover index.

Table A7. Regime dependent connectedness based on QVAR model

	The 0.10-th quantile of oil uncertainty											
	CA	FR	DE	IN	IT	JP	ZA	CH	UK	US	*OIL_UNC*	From
CA	43.17	8.03	2.70	4.29	3.82	1.88	1.59	11.86	0.42	22.18	0.05	56.83
FR	9.78	53.01	3.97	0.64	7.10	3.01	0.11	15.01	0.91	6.44	0.01	46.99
DE	4.42	5.14	71.77	0.45	3.66	1.12	0.07	9.80	0.13	3.41	0.02	28.23
IN	5.74	0.86	0.77	61.60	0.63	0.29	10.11	2.13	5.22	12.57	0.09	38.40
IT	5.44	8.40	3.22	0.44	64.02	3.63	0.04	8.80	0.54	5.43	0.03	35.98
JP	3.79	4.60	1.46	0.10	4.53	76.43	0.05	5.91	0.82	2.30	0.01	23.57
ZA	2.04	0.11	0.06	10.48	0.04	0.03	64.76	0.55	8.83	13.03	0.08	35.24
CH	12.64	12.41	5.91	1.78	6.19	3.21	0.50	47.34	0.16	9.79	0.05	52.66
UK	2.98	1.38	0.58	6.44	0.77	0.80	9.97	1.25	63.92	11.88	0.04	36.08
US	20.44	5.10	2.13	8.32	3.79	1.02	7.48	9.15	5.50	37.03	0.04	62.97
OU	0.05	0.01	0.00	0.00	0.05	0.00	0.01	0.10	0.05	0.01	99.73	0.27
To	67.32	46.04	20.80	32.95	30.58	15.00	29.93	64.54	22.59	87.04	0.42	**37.93**
Net	10.49	-0.95	-7.43	-5.45	-5.39	-8.57	-5.30	11.88	-13.50	24.07	0.15	
	The 0.90-th quantile of oil uncertainty											
	CA	FR	DE	IN	IT	JP	ZA	CH	UK	US	*OIL_UNC*	From
CA	19.21	11.79	6.23	3.22	9.45	8.73	4.50	12.71	5.31	15.22	3.63	80.79
FR5	11.35	19.54	6.43	5.14	10.31	9.16	6.37	12.89	7.57	10.16	1.07	80.46
DE	5.04	5.03	11.88	4.76	4.05	4.67	4.31	5.82	3.76	4.55	46.12	88.12
IN	5.39	6.59	5.57	21.46	6.29	7.80	12.03	6.38	10.03	3.93	14.52	78.54
IT	9.40	10.21	6.13	5.13	18.95	8.69	5.98	10.30	6.72	9.06	9.44	81.05
JP	9.93	10.31	6.02	6.41	9.82	21.70	7.41	10.61	7.89	8.99	0.90	78.30
ZA	7.73	8.76	5.81	11.54	7.36	8.34	20.16	8.62	11.05	5.38	5.26	79.84
CH	12.65	12.10	7.80	4.09	9.92	9.18	5.34	19.76	6.47	11.61	1.08	80.24
UK	6.84	9.25	4.74	11.06	8.40	8.80	12.46	8.07	24.74	3.11	2.51	75.26
US	16.22	11.41	6.65	2.64	9.98	8.82	3.01	13.25	3.88	19.57	4.58	80.43
OU	3.79	3.58	6.52	4.77	2.68	3.75	4.02	4.14	3.14	3.41	60.21	39.79
To	88.34	89.05	61.90	58.76	78.26	77.93	65.43	92.78	65.83	75.42	89.12	**76.62**
Net	7.55	8.59	-26.22	-19.77	-2.79	-0.37	-14.41	12.54	-9.43	-5.01	49.33	

Note: See Notes to Table A1. The table reports the regime dependent connectedness measures computed in similar manner to Diebold and Yilmaz (2012). The lag order of the QVAR models is 1 which is selected by the Bayesian information criterion (BIC) in a linear VAR model. Boldface denotes overall spillover index.

Figure A1. Stock returns and oil uncertainty series

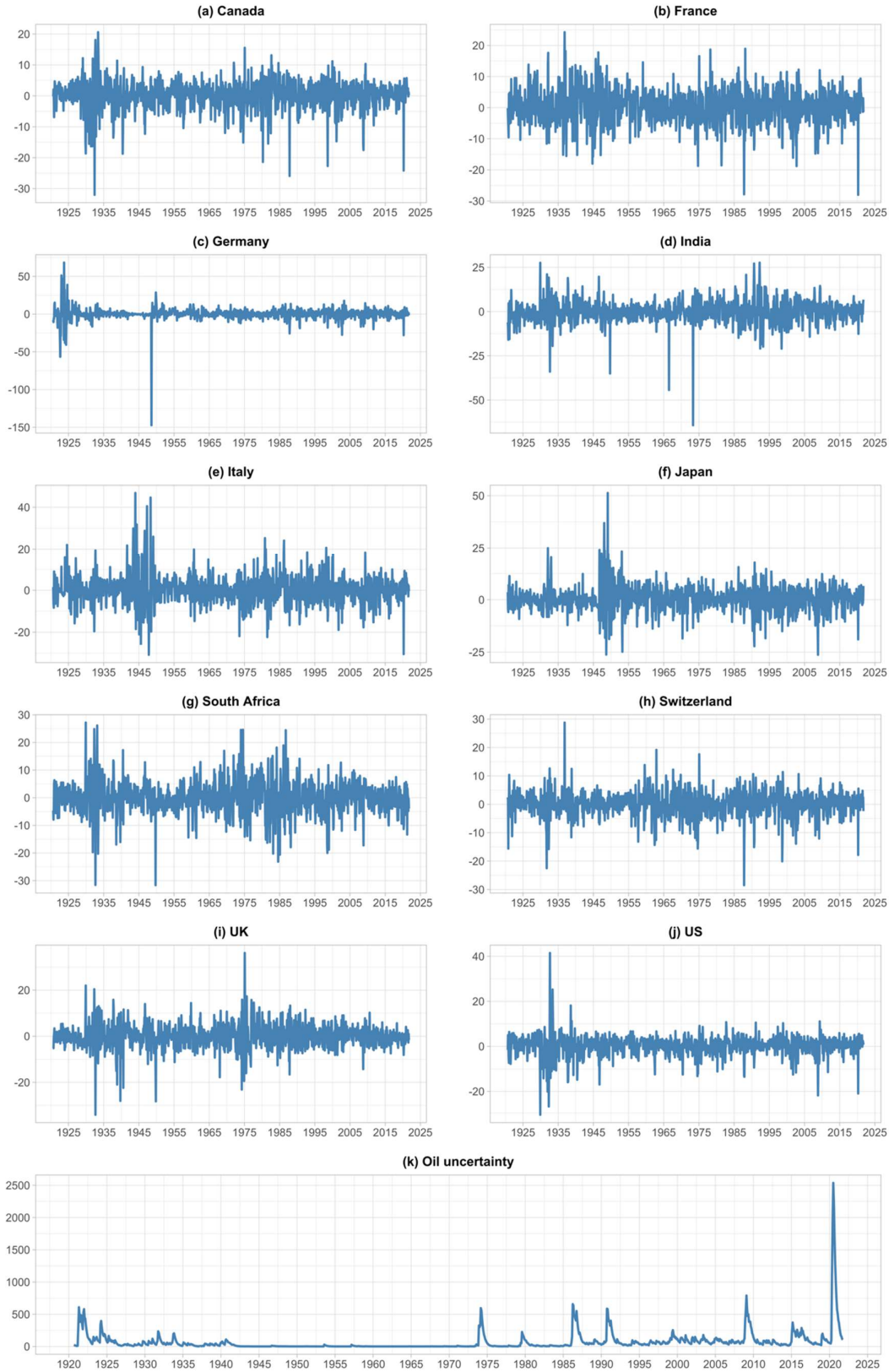
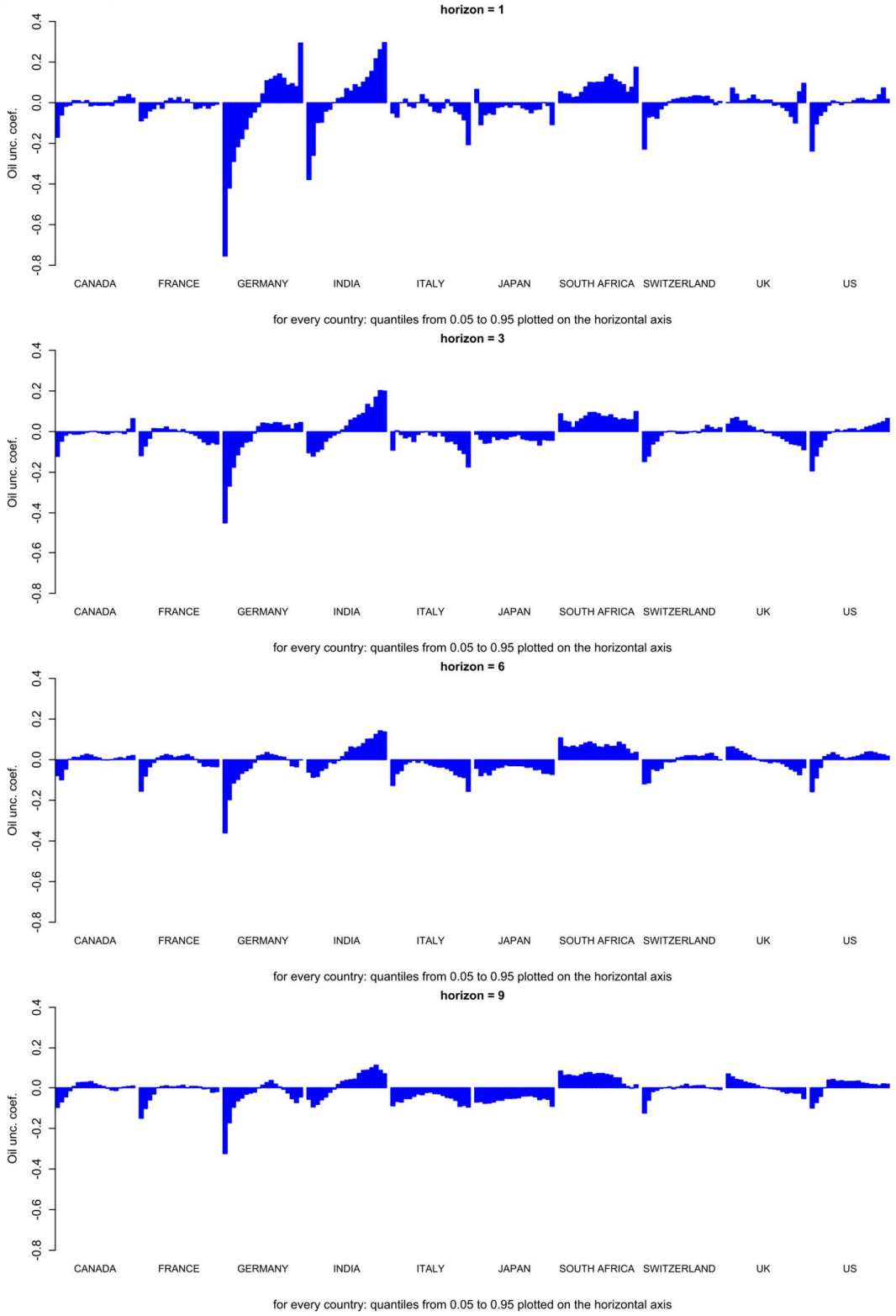
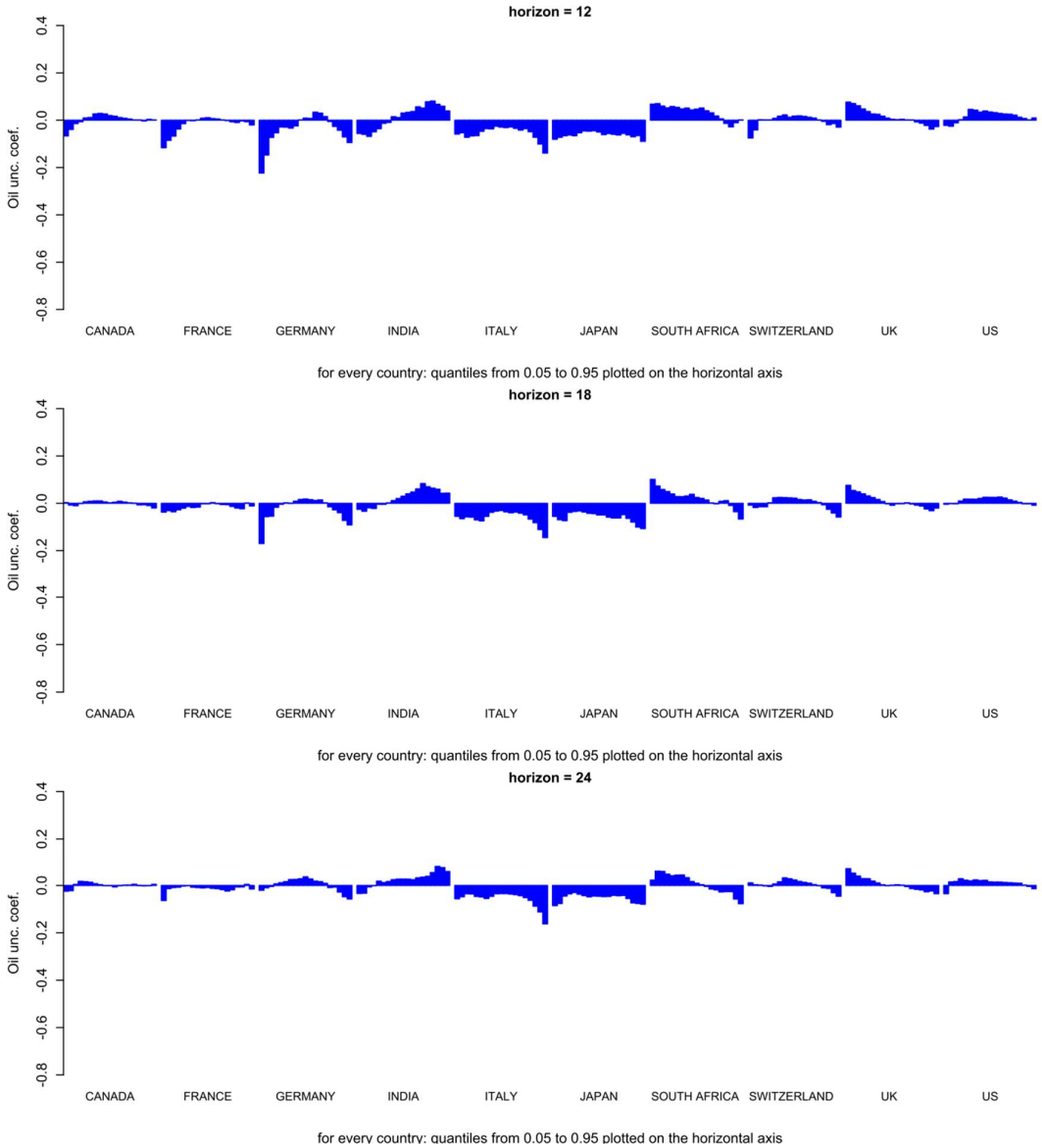


Figure A2. Full-sample quantiles-based response of stock returns to oil price uncertainty (*OIL_UNC*)




horizon = 12
Oil unc. coef.
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
CANADA
FRANCE
GERMANY
INDIA
ITALY
JAPAN
SOUTH AFRICA
SWITZERLAND
UK
US
for every country: quantiles from 0.05 to 0.95 plotted on the horizontal axis
horizon = 18
Oil unc. coef.
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
CANADA
FRANCE
GERMANY
INDIA
ITALY
JAPAN
SOUTH AFRICA
SWITZERLAND
UK
US
for every country: quantiles from 0.05 to 0.95 plotted on the horizontal axis
horizon = 24
Oil unc. coef.
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
CANADA
FRANCE
GERMANY
INDIA
ITALY
JAPAN
SOUTH AFRICA
SWITZERLAND
UK
US
for every country: quantiles from 0.05 to 0.95 plotted on the horizontal axis