Oil-Shocks and Directional Predictability of Macroeconomic Uncertainties of Developed Economies: Evidence from High-Frequency Data

Syed Jawad Hussain Shahzad[*], Rangan Gupta[**], Riza Demirer[***] and Christian Pierdzioch[****]

Abstract

Using high-frequency (daily) data on macroeconomic uncertainties and the partial cross-quantilogram approach, we examine the directional predictability of disentangled oil-price-shocks for the entire conditional distribution of uncertainties of five advanced economies (Canada, Euro Area, Japan, the United Kingdom, and the United States). Our results show that oil-demand, supply, and financial risk-related shocks can predict the future path of uncertainty; however, the predictive relationship is contingent on the initial level of macroeconomic uncertainty and the size of the shocks. Our results suggest that macroeconomic uncertainty is indeed predictable at high frequency, and that oil-price-shocks capture valuable predictive information regarding the future path of macroeconomic uncertainties.

Keywords: Oil shocks, uncertainty, partial cross-quantilograms, directional predictability, developed economies

JEL Codes: C22, C32, Q41

1. Introduction

Uncertainty is a constant challenge for policy makers and investors and measures of uncertainty are key parameters in any type of economic analysis whether it is budget projections, valuation, or risk management. There is no doubt that the global economy has experienced increased macroeconomic and financial uncertainty, especially during the global financial crisis (started in the summer of 2007), followed by a major global recession (termed as "Great Recession") in 2008-09, and regional crises such as the European sovereign debt crisis of 2010. Not surprisingly, the role of uncertainty for macroeconomic fluctuations has emerged as a prominent topic in recent years (see e.g., Chuliá et al., 2017 and Gupta et al., 2018, 2019, 2020, for detailed reviews of this literature). Most of the empirical work on this topic concludes that unexpected large fluctuations in uncertainty (or the closely related concepts of risk and volatility) are an important determinant of macroeconomic (and financial market) fluctuations. In this literature, uncertainty is generally considered to reflect the presence of exogenous factors such as natural disasters or geopolitical turmoil. However, recent evidence suggests that uncertainty is an endogenous response to other macroeconomic forces like aggregate demand and/or supply shocks, hence, amplifying their effects (Mumtaz and Musso, 2019; Ludvigson et al., forthcoming). Furthermore, there is evidence that investors respond to uncertainty in an asymmetric fashion depending on the state of the market

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such that the content of news is concentrated in bad times (e.g., Garcia, 2013), while disagreement among professional forecasters displays a countercyclical pattern (e.g., Cujean and Hasler, 2014).

Given these considerations, a question of paramount importance for policymakers and investors is to determine the possible factors that drive (or possibly predict) uncertainty, since predicting the path of uncertainty, which is a leading indicator (as concluded by the extant literature), would allow policy authorities to determine in which direction the macroeconomy and financial markets are headed, and accordingly decide on the appropriate policy response. In this regard, a series of recent studies (see for example, Kang and Ratti (2013a, 2013b, 2015), Antonakakis et al., (2014), Kang et al., (2017), Degiannakis et al., (2018), Hailemariam et al., (2019)) demonstrate that oil-shocks, in particular aggregate demand innovations, are a major driver of macroeconomic uncertainty, with the transmission operating via direct and indirect channels associated with investment, inflation, production, and the size of the public sector. Against this backdrop, we aim to add to this line of research by revisiting the predictive role of disentangled oil-price-shocks (demand, supply, and financial-market risk shocks), for the uncertainty levels of five advanced countries or regions (Canada, the Euro Area (EA), Japan, the United Kingdom (UK), and the United States (US)), but now, for the first time, at a higher-frequency, i.e., using daily data. Understandably, unlike the existing studies which rely on low-frequency (mainly monthly) data to analyse the role of oil-shocks in driving uncertainty, our analysis at the daily frequency is likely to be relatively more valuable to policymakers, as it will provide more timely high-frequency information regarding the path of uncertainty, which in turn can be fed into nowcasting models (Bańbura et al., 2011) to predict the path of low-frequency macroeconomic as well as financial variables.

This paper analyses the predictability of the daily uncertainty indexes for Canada, the Euro Area (EA), Japan, the United Kingdom (UK), and the United States (US), conditioned upon the size (quantiles) of disentangled oil-shocks using the partial cross-quantilogram approach. The availability of high frequency (daily in our case) uncertainty series, constructed as a real-time measure of uncertainty related to the state of the economy, allows us to explore the predictability of macroeconomic uncertainties at the daily, weekly, and monthly horizons. From an econometric perspective, the structural oil-shocks are derived from a high-frequency Structural Vector Autoregressive (SVAR) model proposed by Ready (2018), and fed into a partial cross-quantilogram (PCQ) of Han et al., (2016), which is a multivariate directional predictive regression model. The PCQ allows us to study the directional impact on the entire distribution of uncertainty conditional on the size of a specific shock, while simultaneously controlling for the other two shocks. Our analysis of oil-price-shocks and uncertainty series over the period of 15th May, 2003 to 31st August, 2018 suggests that oil-price-shocks indeed capture valuable predictive information regarding the future path of macroeconomic uncertainty in developed economies. While the predictive power of oil-demand-shocks is generally more robust across the different economies, we also find significant predictive relationships between oil-supply (and risk shocks) and uncertainty. The predictive relationship, however, is largely concentrated on the extreme high quantiles of oil-price-shocks, suggesting that the predictability of uncertainty can exhibit market-state-based patterns, similar to the case of financial market returns. Nevertheless, our findings suggest that macroeconomic uncertainty is indeed predictable at high frequency and that oil-price-shocks capture valuable predictive information regarding the future path of macroeconomic uncertainties.

The remainder of the paper is organized as follows: Section 2 discusses the data and outlines the SVAR and PCQ methodologies, while Section 3 presents the results, with Section 4 concluding the paper.

2. Data and Methodologies

2.1. Data

We use the daily uncertainty indexes for five developed economies, namely Canada, EA (Euro Area), Japan, the UK, and the US, developed by Scotti (2016).[1] Constructed as a real-time measure of uncertainty related to the state of the economy, these indexes are computed on a daily basis as a weighted average of the squared surprises derived from a set of macroeconomic releases associated with employment, Gross Domestic Product (GDP), industrial production, manufacturing index, personal income, and retail sales, where the weights are based on the contribution of the associated real activity indicator to a business condition index, in line with Aruoba et al., (2009).

In the case of the oil-price demand, supply, as well as risk shocks, we follow Ready (2018) and Demirer et al. (2020) and collect daily price data for the world integrated oil and gas producer index, the nearest maturity NYMEX crude-light sweet oil futures contract, and the Chicago Board Options Exchange (CBOE) volatility index (VIX).[2] We use the nearest maturity NYMEX crude-light sweet oil futures contract as a proxy for the price of crude oil. Finally, we use the innovations in VIX, obtained as the residuals from an ARMA (1,1) model estimated for the VIX index, to capture shocks related to changes in the market discount rate that tend to co-vary with attitudes towards risk.

Our analysis covers the daily period of 15th May, 2003 to 31st August, 2018, with the start and end dates governed by data availability. Table A1 in the Appendix provides the summary statistics for the uncertainty series for each country, as well as the three shock series. We observe that the US experiences the highest level of uncertainty compared to the other developed economies, while the UK and Japan have relatively lower mean and volatility in their daily uncertainty index values. Not surprisingly, the time series plots presented in Figure A1 in the Appendix display a notable spike in the uncertainty series following the 2007/2008 global financial crisis, particularly for the US, UK, and the Euro Area. In the case of the oil-price-shocks, we observe negative mean values for all three shocks series, with notable volatility spikes during the global financial crisis period for the supply and demand shock series. All series display non-normal behavior with large kurtosis values, indicating the presence of extreme observations, thus providing support for our quantile-based analysis.

[1] The uncertainty indexes are available for download from: https://sites.google.com/site/chiarascottifrb/research?authuser=1.

[2] These data are all derived from the Datastream database maintained by Thomson Reuters. The world integrated oil and gas producer index represents the stock prices of global oil producer companies and includes large publicly traded oil producing firms (i.e., BP, Chevron, Exxon, Petrobras or Repsol), but not nationalized oil producers (such as ADNOC or Saudi Aramco).

2.2. Methodologies

The econometric framework we use in our empirical analysis consists of two components. First, we rely on the methodology introduced by Ready (2018) to decompose oil-price changes into demand, supply and risk driven shocks. Second, we use the PCQ approach of Han et al., (2016) to examine the directional predictability of the uncertainty indexes by incorporating the information captured by the three oil-price-shock series.

2.2.1. Identification of Oil-Price-Shocks

In a well-cited study, Kilian (2009) highlights the importance of distinguishing between supply and demand related shocks in order to get a more accurate assessment of oil-price effects on variables of concern. Clearly, supply, and demand driven shocks embedded in oil-price fluctuations reflect different information regarding market dynamics and economic expectations. While demand shocks could be more reflective of investors' expectations of future economic growth prospects, supply shocks could be more related to geopolitical developments. Furthermore, any effect of oil-price fluctuations on stock returns of oil companies should be assessed after controlling for non-cash flow related factors, captured by innovations to risk sentiment among investors, which in turn is likely to drive overall macroeconomic uncertainty dur to macr-financial linkages. Given this, Ready (2018) develops a model to decompose oil-price-shocks into demand, supply, and risk related components at a high-frequency (unlike Kilian's (2009) model based on monthly data) based on the following matrix form:

$$X_t = AZ_t \tag{1}$$

where $X_t = \left[\Delta oil_t, R_t^{Prod}, \xi_{VIX,t}\right]'$ is a 3×1 vector, Δoil_t denotes the change in oil-price in period t, R_t^{Prod} is the return on the global stock index of oil producing firms, and $\xi_{VIX,t}$ stands for the innovation to the VIX, based on an ARMA(1,1) specification. Our focus is $Z_t = [s_t, d_t, v_t]'$, which is a 3×1 vector of oil-supply, demand, and risk shocks represented by s_t, d_t and v_t, respectively. Finally, A is a 3×3 matrix of coefficients defined as:

$$A = \begin{bmatrix} 1 & 1 & 1 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix} \tag{2}$$

Then, Ready (2018) imposes the following condition to achieve orthogonality among the three types of shocks as follows:

$$A^{-1}\Sigma_X(A^{-1})^T = \begin{bmatrix} \sigma_s^2 & 0 & 0 \\ 0 & \sigma_d^2 & 0 \\ 0 & 0 & \sigma_v^2 \end{bmatrix} \tag{3}$$

where Σ_X denotes the covariance matrix of the variables in X_t, while σ_s^2, σ_d^2 and σ_v^2 are the variance of the supply, demand, and risk shocks, respectively.

Intuitively, Ready (2018) defines demand shocks as the portion of returns on a global stock index of oil producing firms that is orthogonal to the innovations of the VIX, with these innovations considered to control for aggregate changes in market discount rates that affect stock returns of oil producing companies, and hence are used as a proxy for risk shocks. Supply shocks, in turn, are represented by the residual component of oil-price changes that is orthogonal to both demand shocks and risk shocks.

2.2.2. Partial Cross-Quantilogram (PCQ)

We follow Han et al. (2016) to analyze the effect of a particular oil-shock on economic uncertainty by simultaneously controlling for the other two shocks derived from the SVAR. Like the cross-quantilogram (CQ) method, the PCQ approach also measures the serial dependence between two events $x_{1t} \leq q_{1,t}(\tau_1)$ and $x_{2,t-k} \leq q_{2,t-k}(\tau_2)$. Additionally, the PCQ controls for any intermediate events between time points t and $t - k$. Assume $z_t \equiv [\psi\left(\mathrm{x}_{\tau_3}\left(x_{3t} - q_{3,t}(\tau_3)\right), \dots, \psi\left(x_{lt} - q_{l,t}(\tau_l)\right)\right]^{\intercal}$, where z_t is a vector that can include lagged predictor variables (for example, oil-demand-shock) and economic state variables (for example, the other two oil-shocks, i.e., oil-supply and risk shocks). Assuming $\bar{x}_{1,t} = \left[x_{1,1t,\dots}x_{1,lt}\right]^{\intercal}$ and $\bar{x}_{2,t} = \left[x_{2,1t,\dots\dots}x_{2,lt}\right]^{\intercal}$, the correlation matrix of the hit processes and corresponding inverse matrix can be presented in the following manner:

$$R_{\bar{\tau}}^{-1} = E[h_t(\bar{\tau})h(\bar{\tau})^{\intercal}]^{-1} = P_{\bar{\tau}} \tag{4}$$

where $h_t(\bar{\tau}) = \left[\psi\left(x_{1t} - q_{1,t}(\tau_1)\right), \dots, \psi_{\tau l}\left(x_{lt} - q_{l,t}(\tau_l)\right)\right]^{\intercal}$ denotes the quantile hit process and the PCQ is defined as:

$$\rho_{\bar{\tau}|z} = -p_{\bar{\tau},12}/\sqrt{p_{\bar{\tau},11}p_{\bar{\tau},22}} \tag{5}$$

The PCQ $\rho_{\bar{\tau}|z}$ can also take a form $\rho_{\bar{\tau}|z} = \delta\sqrt{\frac{\tau_1(1-\tau_1)}{\tau_2(1-\tau_2)}}$, where δ represents a scalar parameter which can be defined using the following regression equation:

$$\psi\left(x_{1t} - q_{1,t}(\tau_1)\right) = \delta\psi_{\tau 2}\left(x_{2t} - q_{2,t}(\tau_2)\right) + \gamma^{\intercal}z_t + u_t$$

Under the null hypothesis $\rho_{\bar{\tau}|z} = 0$, we essentially test the directional predictability (being a correlations-based test) between two quantile hits conditional on the information embedded in z_t. This test is analogous to the regression-form causality proposed by Granger (1969).

3. Empirical Results

Figures 1-3 present the partial cross-quantile dependence estimates that measure the directional predictability to uncertainty from oil-demand, supply, and risk shocks. In all figures, we, following Shahzad et al., (forthcoming), control for the effect of the remaining shock variables by fixing them at a quantile level of 0.05.[3] For example, in Figure 1, the PCQ estimates represent the spillover effects from oil-demand-shocks to uncertainty series conditioned on oil-supply and risk shocks fixed at 0.05 quantile. In each partial cross-quantilogram, the horizontal (vertical) axis displays the quantiles of oil-shocks (uncertainty). Panels A, B, and C present the findings for the predictive relationships at lags 1, 5, and 22 days, roughly corresponding to daily, weekly, and monthly predictive horizons.

[3] Our results are qualitatively similar if the additional shocks used as controls are fixed at their median or a quantile value of 0.05. Complete details of these results are available upon request from the authors.

A visual comparison of PCQs across the three oil shock series in Figure 1 to 3 indicates that oil-demand-shocks generally have stronger predictive power over economic uncertainty, compared to oil-supply and risk shocks. This is not unexpected as, by construction, oil-demand-shocks measure fluctuations in oil-prices implied by an index of stock prices for global oil-producing companies. Considering that the stock market valuations are generally considered to be a leading indicator of economic activity, it is not surprising to see that demand shocks that are inferred from stock valuations of global oil producing firms capture relatively stronger predictive information compared to supply and risk shocks. However, examining the PCQs for oil-demand-shocks in Figure 1, we observe that the predictive relationship is largely restricted to the high quantiles of demand shocks only, displayed on the horizontal axis. This suggests that the predictive information captured by oil-demand-shocks is limited to extreme positive values of these shocks such that large positive fluctuations in oil-prices driven by demand side factors capture significant predictive power over economic uncertainty. Considering that a positive demand shock would be associated with a rise in global demand for oil, favourable economic growth projections and investor sentiment, the strong predictive patterns observed particularly at extreme high demand shock quantiles suggest uncertainty is generally more significantly associated with unexpected positive market uncertainties, rather than negative uncertainties. This is indeed interesting given the evidence reported by Huang et al. (2017) that stock-return predictability generally concentrates in bad times rather than in good times as disagreement spikes during bad times (e.g. Patton and Timmermann, 2010). To that end, it can be argued that boom market states, implied by large positive oil-demand-shocks, capture predictive information over the uncertainty state of the economy; however, the predicted direction of uncertainty is not clear as indicated by the positive and negative relationship observed at high quantiles of demand shocks (implied by the blue and red regions in the plots).

Further examining the predictive relationships between oil-demand-shocks and uncertainty in Figure 1 indicates an asymmetric pattern with respect to uncertainty quantiles. While the predictive relationship between demand shocks and uncertainty is positive when both series are at extreme high quantiles, the opposite is observed at the extreme low quantiles of uncertainty. With the exception of Japan, we observe that large positive oil-price fluctuations driven by demand side factors capture information associated with both high and low uncertainty states regarding the macroeconomic conditions. While the positive association between oil-demand-shocks and macroeconomic uncertainties can be explained by economic fundamentals that drive demand shocks in oil-prices, it can also be explained by the finding that the content of news is concentrated in bad times (e.g., Garcia, 2013) and by the fact that disagreement among professional forecasters moves in a countercyclical fashion (e.g., Patton and Timmermann, 2010). Accordingly, the positive directional predictability from oil-demand-shocks to macroeconomic uncertainty, particularly at extreme high quantiles of demand shocks, may be a manifestation of the countercyclicality in disagreement and how information is processed among market participants during good times. Similarly, lower uncertainty predicted by large positive oil-demand-shocks can be a manifestation of lower degree of uncertainty in economic activity during boom market states. Nevertheless, the analysis of demand shocks suggests that oil booms driven by demand side factors capture valuable predictive information about the level of uncertainty in subsequent periods.

Examining the findings for oil-supply-shocks, presented in Figure 2, we observe that the predictive relationship generally holds for the Euro Area, Japan, the UK, and the US, with the effect being particularly strong for the latter two countries corresponding to the upper quantiles of uncertainty, and for nearly all quantiles of oil-supply-shocks. Recall that, by construction, oil-supply-shocks capture increases in oil-prices due to disruption in oil production. In light of this, one would expect that oil-supply-shocks are likely to be positively related with uncertainty. In Figure 2, we observe that the positive impact of oil-supply-shocks on uncertainty for the UK and US is generally widespread at high quantiles of uncertainty, while the positive effect is primarily restricted to the lower quantiles of uncertainty for Japan. Clearly, oil-price fluctuations due to supply disruptions have a greater positive effect on macroeconomic uncertainties for the US, and to some extent for the UK; however, the effect on Canada and Japan is rather limited, suggesting that the predictive information captured by demand shocks contain idiosyncratic components that affect countries heterogeneously. The negative relationship observed at low quantiles of uncertainty could reflect the fact that supply disruptions in the oil market lead to a reduction in trading and hence, lower the volatility and associated uncertainty in the oil sector (Degiannakis et al., 2018). This, in turn, tends to reduce overall macroeconomic uncertainty (primarily at its lower conditional quantiles), given the well-established nexus between oil and the real economy at the levels of both first- and second-moments (Hailemariam et al., 2019).

Finally, the findings in Figure 3 show that the relationship between oil-price hikes associated with financial market risk shocks and uncertainty holds for most countries in the sample with the effect being particularly strong for the UK and the US. The positive predictive relationship between risk shocks and uncertainty is largely concentrated at the upper quantiles of uncertainty, and for nearly all sizes of the oil-supply-shock. This is indeed consistent with evidence suggesting that financial market risk shocks (resulting in oil-price hikes, and its volatility (Bonaccolto et al., 2018)) spill over to the real economy and foster macroeconomic uncertainty (Gabauer and Gupta, 2020). This is generally what is observed for Canada (at higher quantiles of both uncertainty and the risk shocks), the UK, the US, and somewhat for Japan (with the effect being restricted primarily at the lower quantiles for all these three countries for moderate levels of the risk shock).

[INSERT FIGURES 1 TO 3]

In sum, the evidence suggests that oil-price-shocks associated with demand, supply side factors as well as financial market risk shocks capture valuable predictive information regarding macroeconomic uncertainties in the developed economies analysed. The effect, however, is generally contingent on the initial level of uncertainty and the size of the shocks captured by the various quantiles. Furthermore, Canada, the UK, and the US, which play important roles both in the exporting and importing fronts of the oil market, seem to be affected relatively more by the various oil-price-shocks compared to the net importers in the Euro Area and Japan. Finally, given the evidence that the impact of oil shocks on uncertainty can be time-varying (Degiannakis et al., 2018), we also estimated the PCQs based on a rolling-window estimation of 1000 observations. As shown in Figures A2 to A4 in the Appendix, the inferences derived from the full-sample estimation continues to hold, in general, with the predictive relationship strengthening over time.

4. Conclusion

Uncertainty is a key element of decision-making, investments and valuation, hence timely and high frequency prediction of uncertainty is invaluable to investors and policymakers in gauging the future path of low-frequency metrics of economic activity. The availability of high-frequency (daily in our case) uncertainty series, constructed as a real-time measure of uncertainty related to the state of the economy, allows us to explore the predictability of macroeconomic uncertainties at the daily, weekly and monthly horizons. Given this, we analyse the predictability of the daily uncertainty indexes for Canada, the Euro Area (EA), Japan, the United Kingdom (UK), and the United States (US), conditioned upon the size (quantiles) of disentangled oil shocks using the partial cross-quantilogram approach. Daily data covering the period of 15th May, 2003 to 31st August, 2018, reveals that, in particular, large oil-demand and oil-supply-shocks, as well as innovations associated with financial market risks can indeed provide valuable information regarding the future path of macroeconomic uncertainty. The direction of predictability is however, contingent on the size of uncertainty captured by the quantile-based models. While the observed predictive relationship between oil-price-shocks and macroeconomic uncertainty can be explained by the well-documented link between oil-prices and the macroeconomy, it is also possible that countercyclicality in professional forecasters' disagreement also plays a role in the asymmetries in the predictability of uncertainty due to large oil-price-shocks.

As part of future research, it would be interesting to extend our analysis to an out-of-sample forecasting exercise, given that in-sample predictability does not guarantees out-of-sample forecasting gains. Another area of further research could involve re-conducting our analysis, contingent on availability, on daily uncertainty data for emerging markets. Finally, one could also explore the channels in which disentangled oil-price-shocks predict the future path of uncertainty series during good and bad market states.

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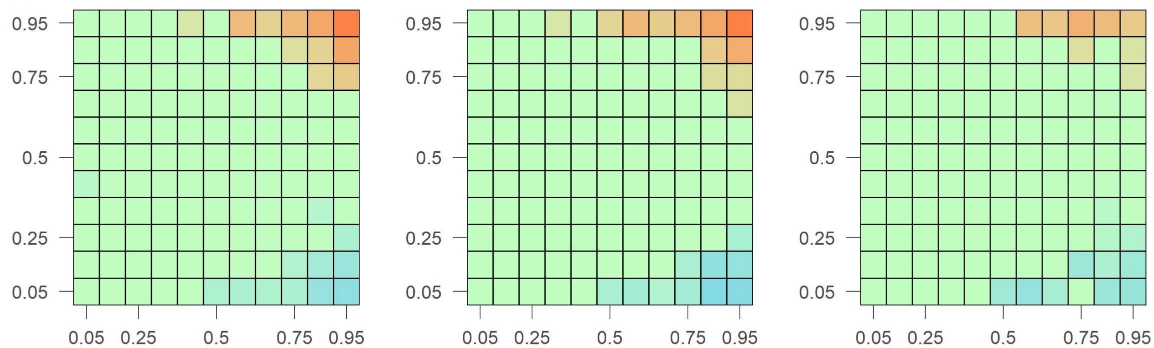
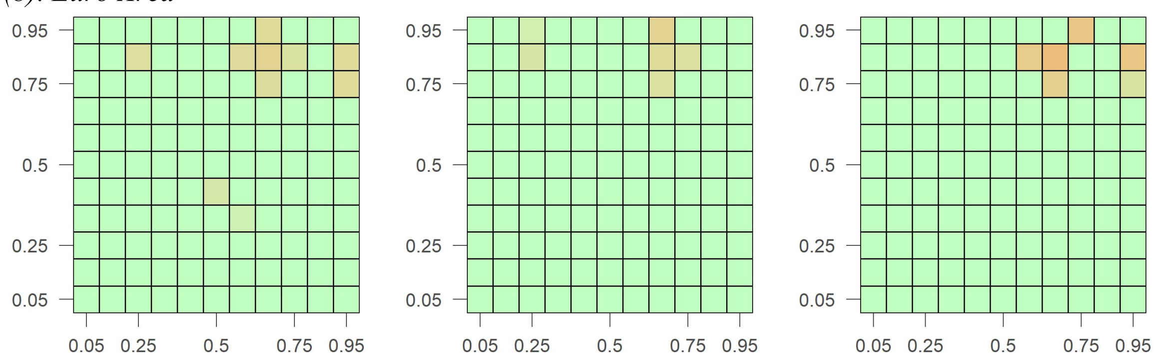
Figure 1. Partial cross-quantilograms (PCQ) for the directional predictability from *oil-demand-shocks* to uncertainty.

Panel A: lag =1 day **Panel B:** lag =5 day **Panel B:** lag =22 day

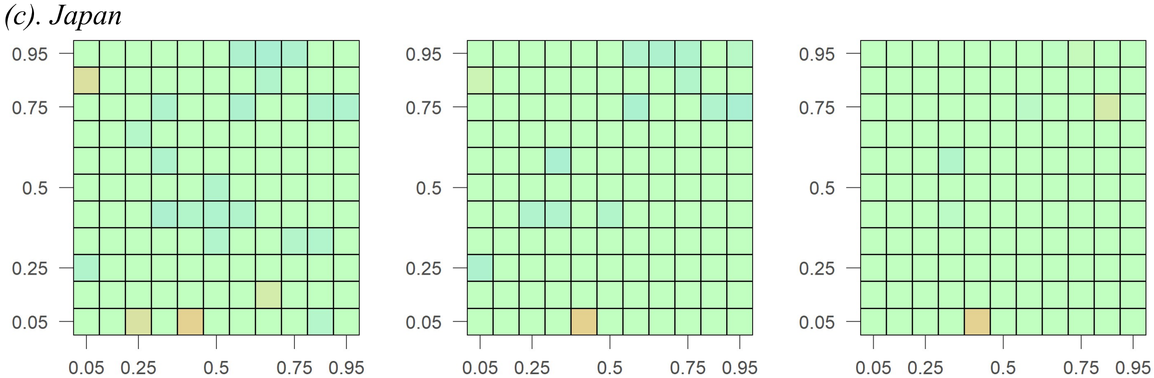
(a). Canada



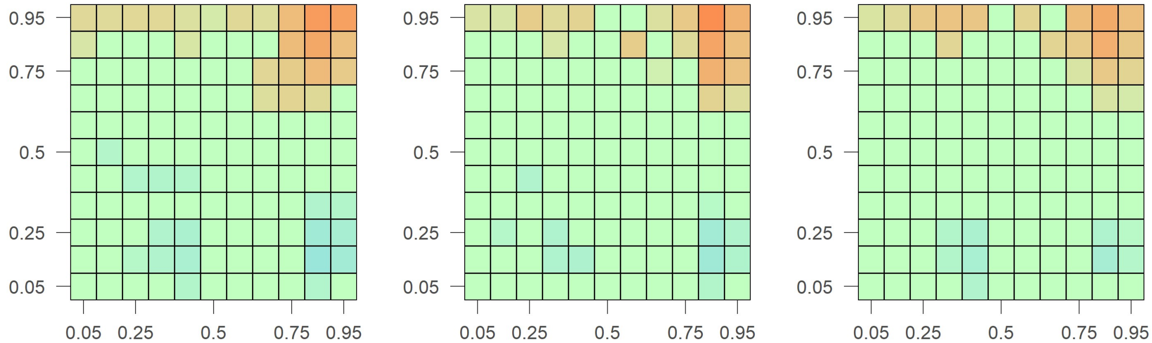
(b). Euro Area



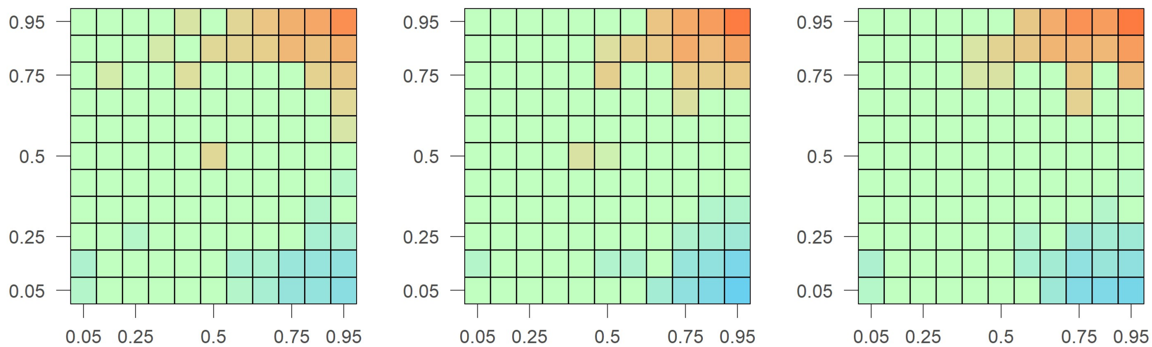
(c). Japan



(d). United Kingdom (UK)



(e). United States (US)



Note: The figures present the directional predictability at various quantiles (via partial cross-quantilograms that represent partial cross-quantile dependence) from *oil-demand-shocks* to uncertainty, after controlling for oil-supply and risk shocks (fixed at quantile 0.05). In each partial cross-quantilogram, the horizontal (vertical) axis displays the quantiles of oil-demand-shock (uncertainty). The full sample period is from 15th May, 2003 until 31st October, 2018 comprising of 4,035 daily observations. The colour bar indicates the sign and magnitude of the significant predictive relationships (at 5% level) between the variables. The null hypothesis of no return predictability is tested based on 1,000 bootstrap iterations.

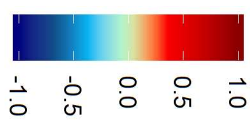
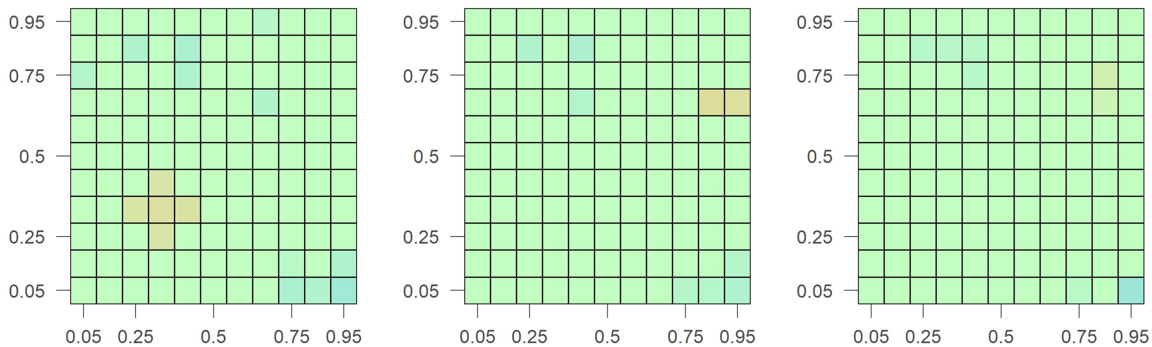


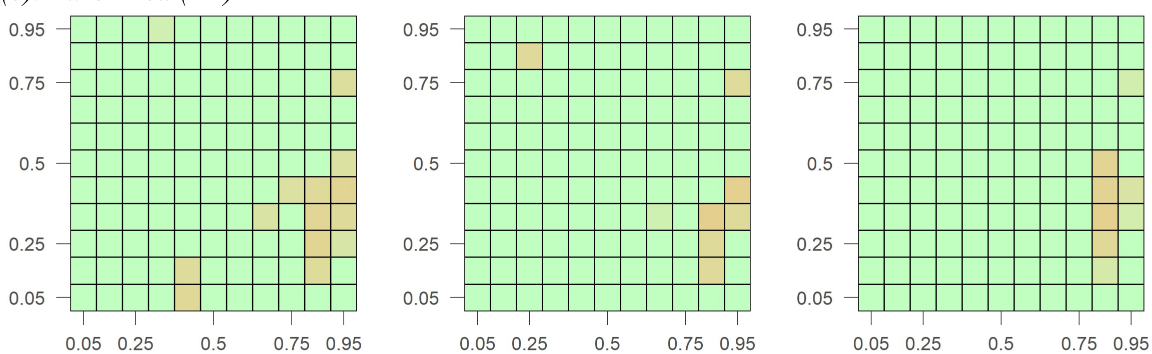
Figure 2. Partial cross-quantilograms (PCQ) for the directional predictability from *oil-supply-shocks* to uncertainty.

Panel A: lag =1 day | **Panel B:** lag =5 day | **Panel B:** lag =22 day

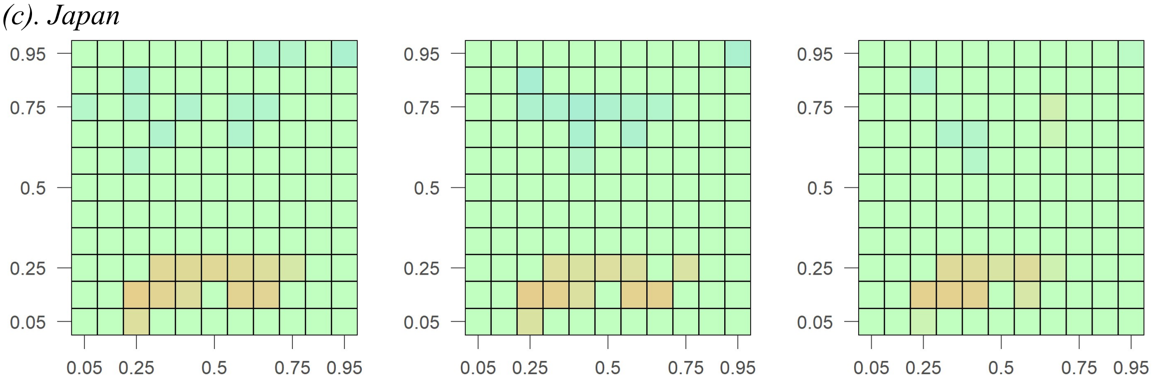
(a). Canada



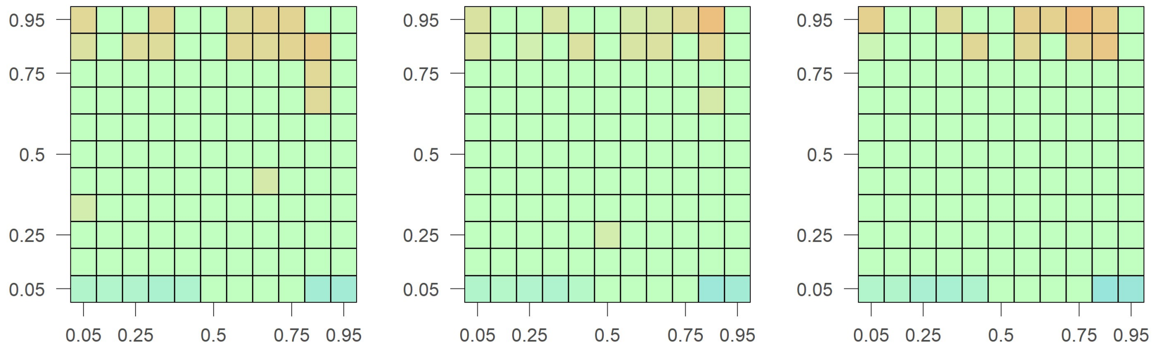
(b). Euro Area (EA)



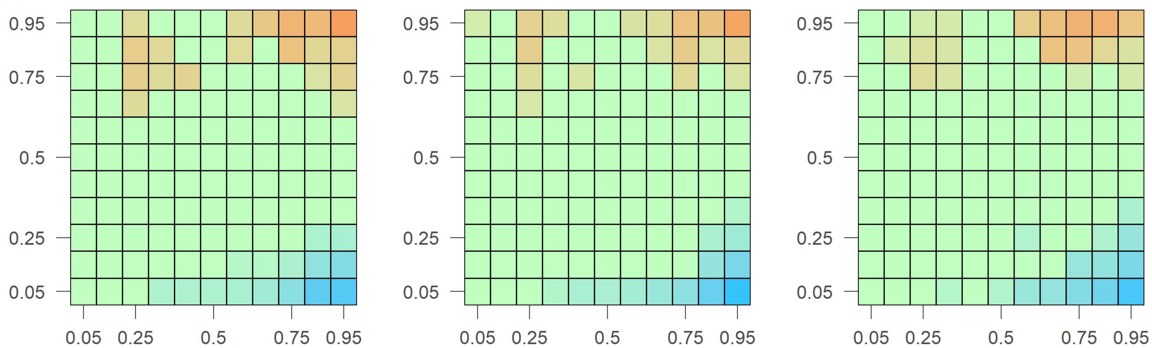
(c). Japan



(d). United Kingdom (UK)



(e). United States (US)



Note: The figures present the directional predictability at various quantiles (via partial cross-quantilograms that represent partial cross-quantile dependence) from *oil-supply-shocks* to uncertainty, after controlling for oil-demand and risk shocks (fixed at quantile 0.05). In each partial cross-quantilogram, the horizontal (vertical) axis displays the quantiles of oil-demand-shock (uncertainty). See notes to Figure 1.

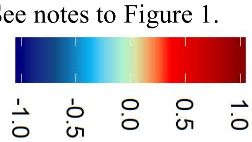
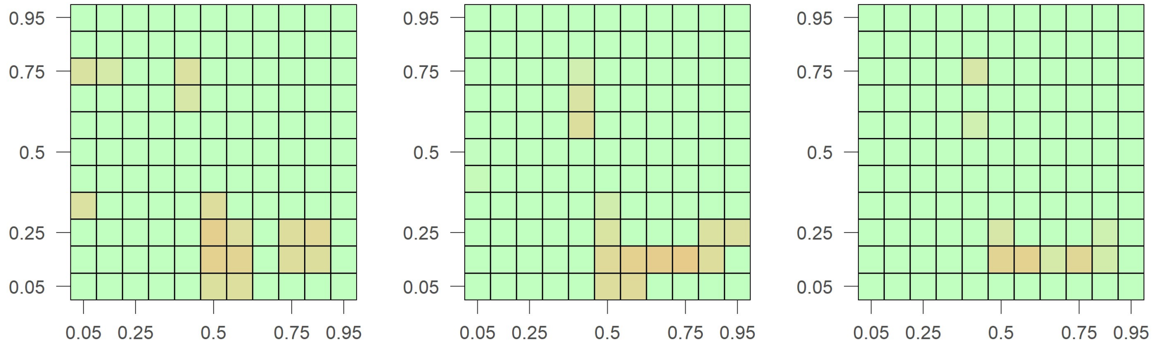
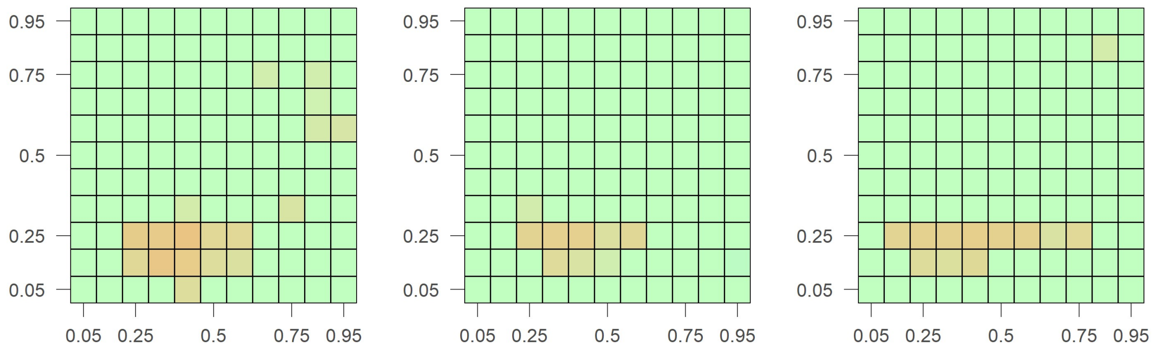


Figure 3. Partial cross-quantilograms (PCQ) for the directional predictability from *risk shocks* to uncertainty.

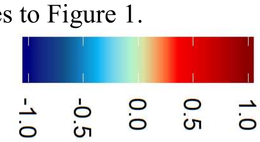
(d). United Kingdom (UK)



(e). United States (US)



Note: The figures present the directional predictability at various quantiles (via partial cross-quantilograms that represent partial cross-quantile dependence) from *risk shocks* to uncertainty, after controlling for oil-demand and supply shocks (fixed at quantile 0.05). In each partial cross-quantilogram, the horizontal (vertical) axis displays the quantiles of risk shock (uncertainty). See notes to Figure 1.



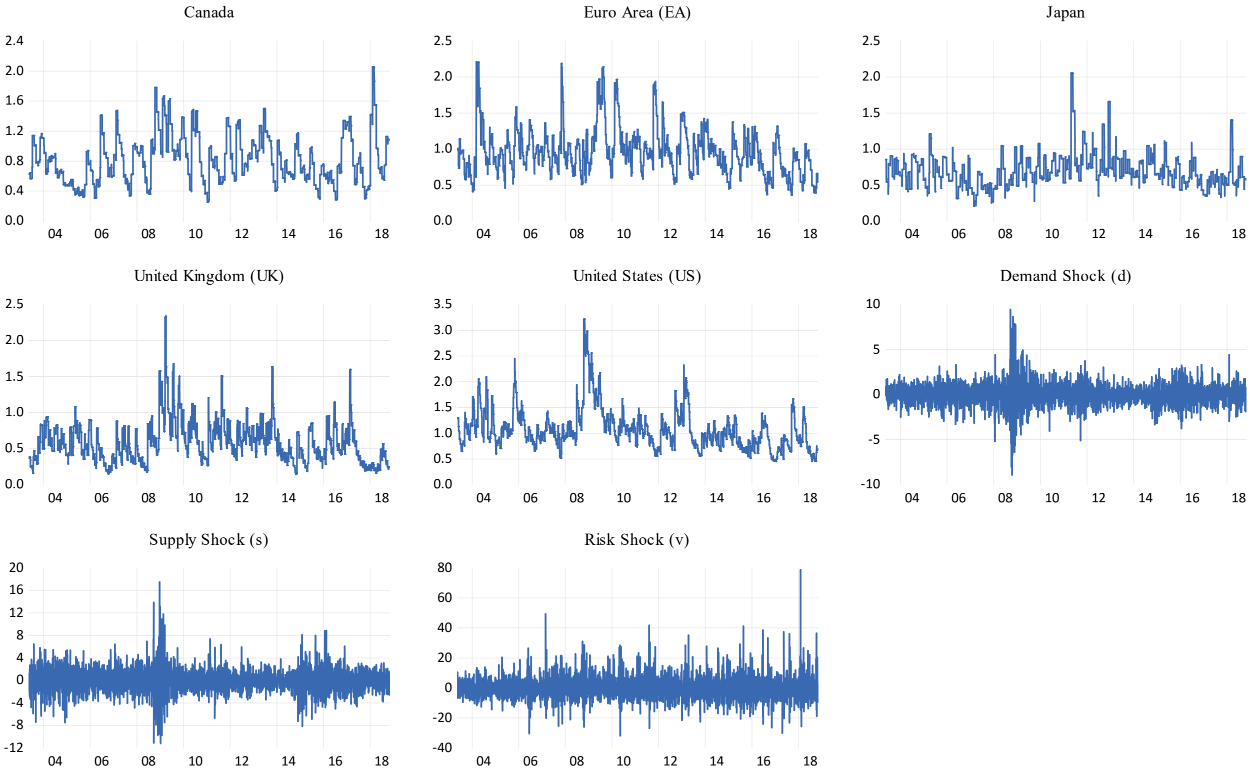
APPENDIX

Table A1. Summary Statistics.

	Canada	Euro Area (EA)	Japan	United Kingdom (UK)	United States (US)	Demand Shock (*d*)	Supply Shock (*s*)	Risk Shock (*v*)
Mean	0.8218	0.9731	0.6970	0.5898	1.0796	-0.0044	-0.0014	-0.1031
Median	0.7669	0.9404	0.6545	0.5354	1.0021	0.0199	-0.0055	-0.6343
Max.	2.0563	2.2074	2.0570	2.3385	3.2167	9.4707	17.4887	78.6970
Min.	0.2530	0.3621	0.2071	0.1466	0.4493	-8.9221	-11.1947	-31.9383
S.D.	0.3309	0.3267	0.2374	0.2942	0.4055	1.1255	1.8921	6.9497
Skewness	0.6985	1.1032	1.7675	1.4110	1.7042	0.0413	0.3138	1.1987
Kurtosis	3.2021	4.8220	9.4055	6.8123	7.5525	11.1051	9.3737	11.2329
JB	334.942	1376.677	8999.169	3782.247	5437.600	11045.580	6896.147	12362.040
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
N				4035				

Note: This table presents the summary statistics for the daily uncertainty indexes for five developed economies (Canada, EA (Euro Area), Japan, the UK and the US) per Scotti (2016) and the oil-demand, supply and risk shocks per Ready (2018). Max., Min., S.D., JB, *p*-value and *N* are the maximum, minimum, standard deviation, Jarque-Bera test of normality, the probability of the null of normality under the JB test and the number of observations, respectively.

Figure A1. Data Plots.

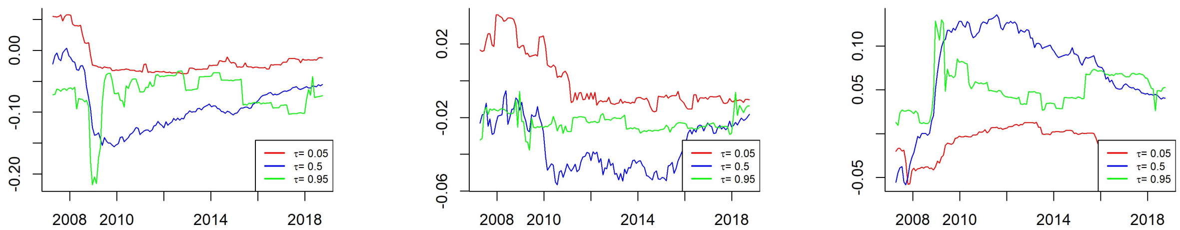


Note: The figures present the time series plots for the daily uncertainty indexes for five developed economies (Canada, EA (Euro Area), Japan, the UK and the US) per Scotti (2016) and the oil-demand, supply and risk shocks per Ready (2018).

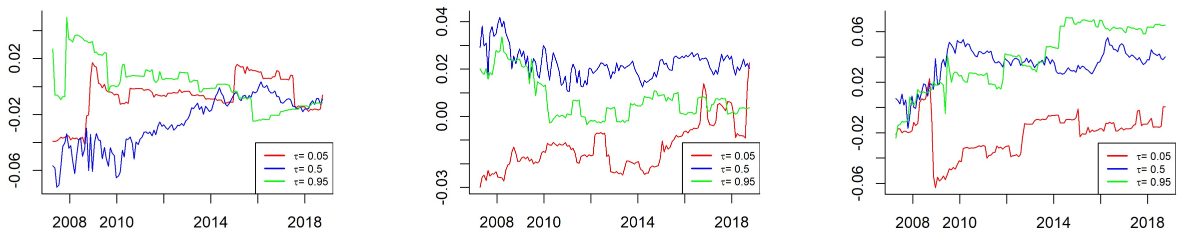
Figure A2. Rolling-Window Partial Cross-Quantilograms (PCQ) for *Oil-Demand-Shocks*.

Panel A: α*=0.05* **Panel B:** α*=0.50* **Panel C:** α*=0.95*

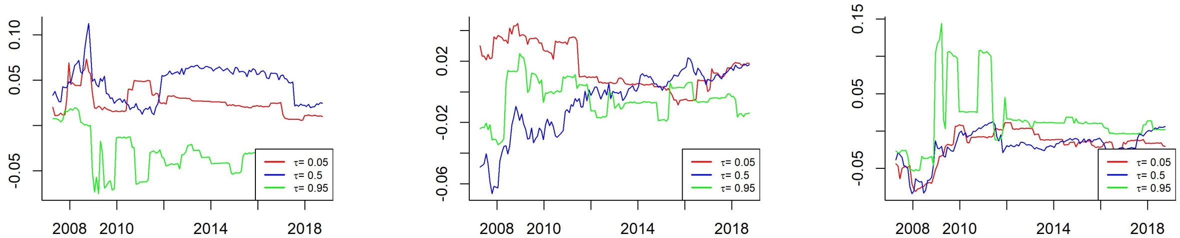
(a). Canada



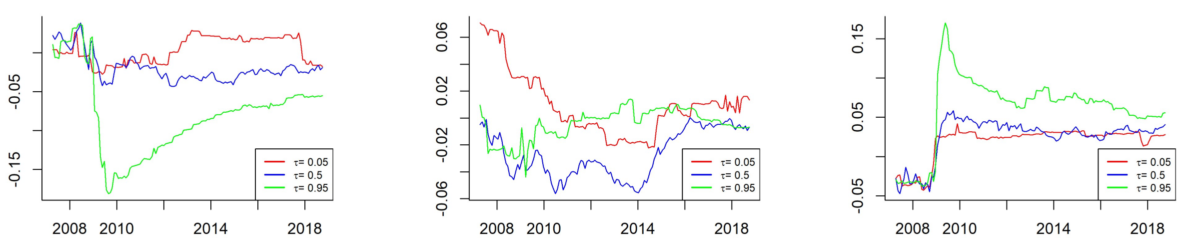
(b). Euro Area (EA)



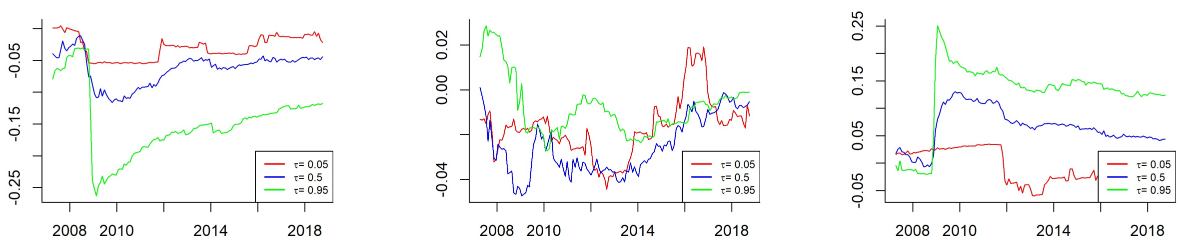
(c). Japan



(d). United Kingdom (UK)



(e). United States (US)

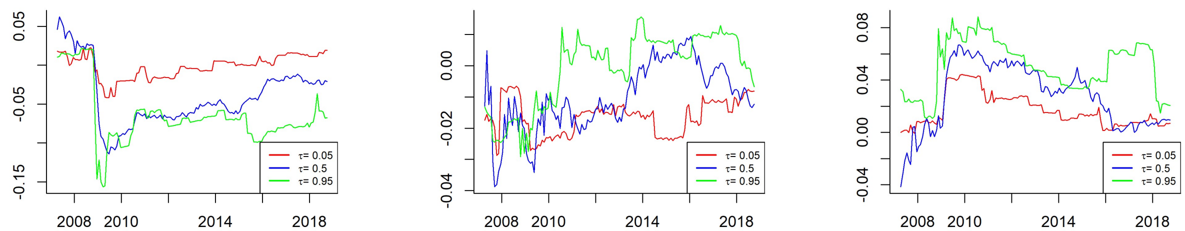


Note: The figures present rolling window based directional predictabilities (via partial cross-quantilograms that represent cross-quantile dependence) for selected quantiles from *oil-demand*-shocks to uncertainty, after controlling for oil-supply and risk shocks (fixed at the quantile level of 0.05). Panels A, B and C show the 1-day ahead rolling spillover estimates for the lowest (α=0.10), middle (α =0.50), and highest (α =0.90) quantiles, respectively. The starting year of the rolling window is marked on the horizontal axis. We use recursive-rolling (1000-day fixed window and a step size of 22 days).

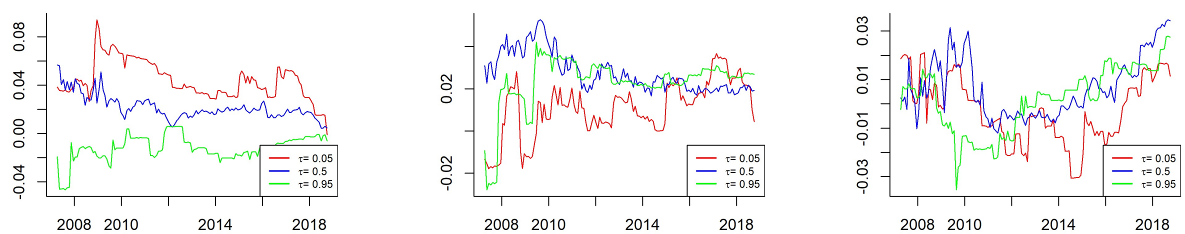
Figure A3. Rolling-Window Partial Cross-Quantilograms (PCQ) for *Oil-Supply-Shocks*.

Panel A: *α=0.05* **Panel B:** *α=0.50* **Panel C:** *α=0.95*

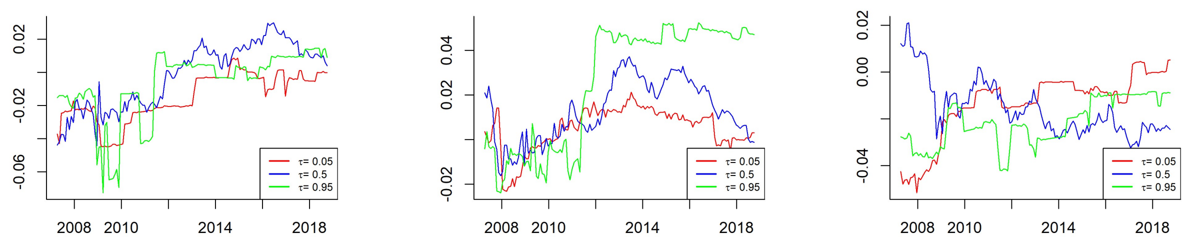
(a). Canada



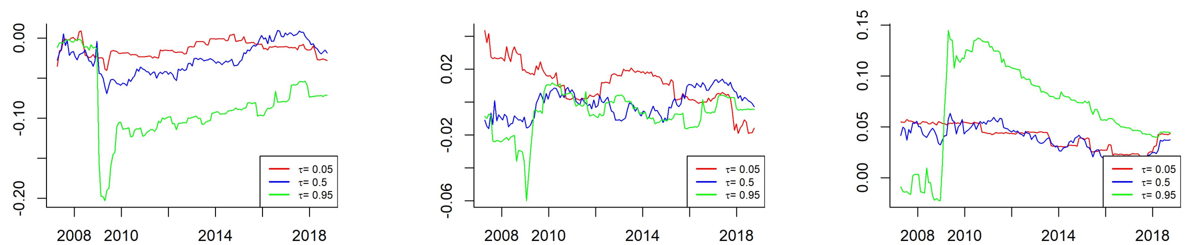
(b). Euro Area (EA)



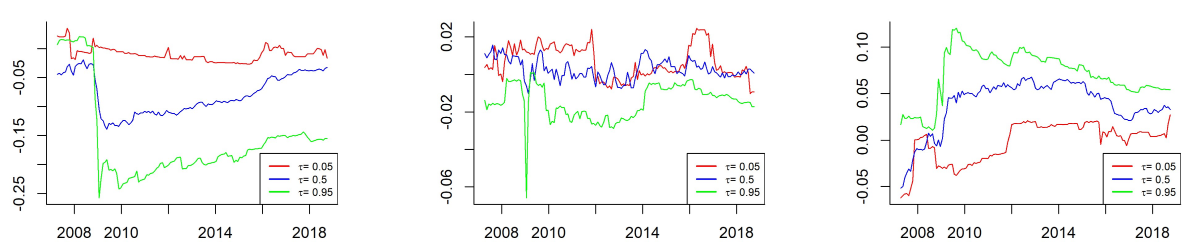
(c). Japan



(d). United Kingdom (UK)



(e). United States (US)

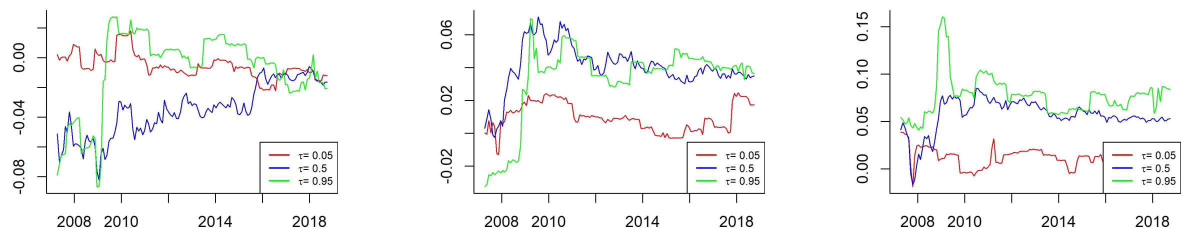


Note: The figures present rolling window based directional predictabilities (via partial cross-quantilograms that represent cross-quantile dependence) for selected quantiles from *oil-supply*-shocks to uncertainty, after controlling for oil-demand and risk shocks (fixed at the quantile level of 0.05). See notes to Figure A2.

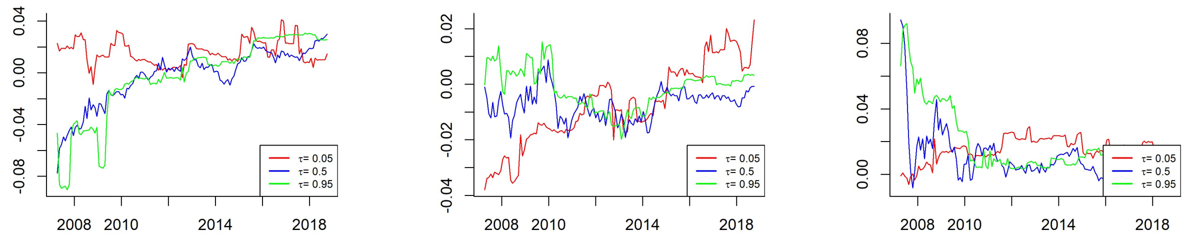
Figure A4. Rolling-Window Partial Cross-Quantilograms (PCQ) for *Risk Shocks*.

Panel A: α=*0.05* Panel A: α=*0.50* Panel A: α=*0.95*

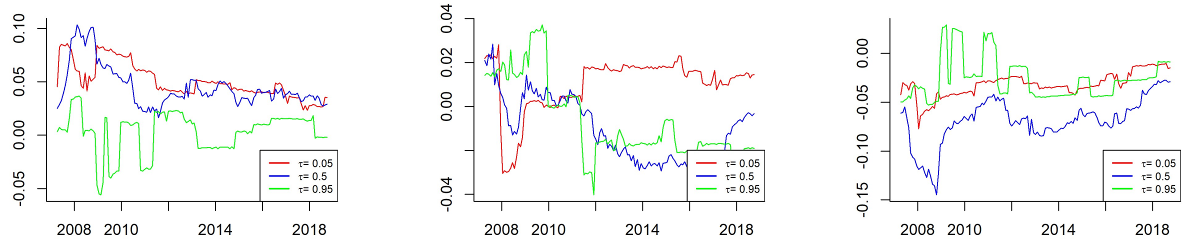
(a). Canada



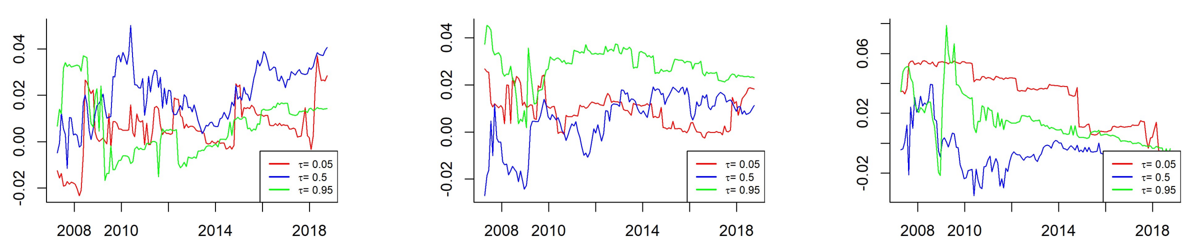
(b). Euro Area (EA)



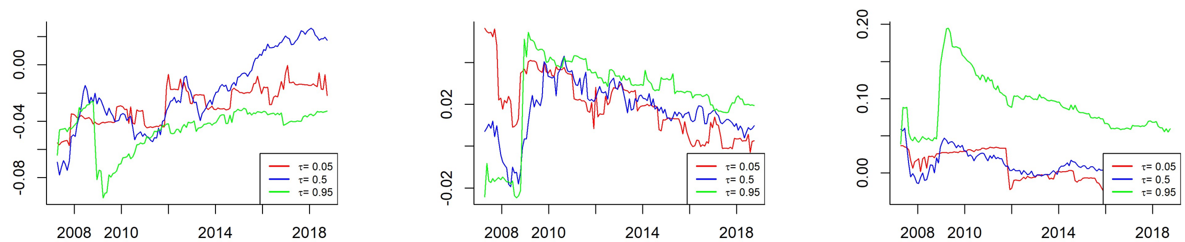
(c). Japan



(d). United Kingdom (UK)



(e). United States (US)



Note: The figures present rolling window based directional predictabilities (via partial cross-quantilograms that represent cross-quantile dependence) for selected quantiles from *risk* shocks to uncertainty, after controlling for oil-supply and demand shocks (fixed at the quantile level of 0.05). See notes to Figure A2.