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# The dynamic impact of uncertainty in causing and forecasting the distribution of oil returns and risk[☆]

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## HIGHLIGHTS

- We study time-varying quantile causality of EMU and EPU for oil returns and risk.
- We compare squared returns and realized variance in studying causality in oil risk.
- We accompany the causality exercise with a forecasting analysis.
- Evaluation of in- and out-of-sample performance using various suitable tests.
- We highlight heterogeneous effects of EPU and EMU on the oil movements distribution.

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## ABSTRACT

The aim of this study is to analyze the relevance of recently developed news-based measures of economic policy and equity market uncertainty in causing and predicting the conditional quantiles of crude oil returns and risk. For this purpose, we studied both the causality relationships in quantiles through a non-parametric testing method and, building on a collection of quantiles forecasts, we estimated the conditional density of oil returns and volatility, the out-of-sample performance of which was evaluated by using suitable tests. A dynamic analysis shows that the uncertainty indexes are not always relevant in causing and forecasting oil movements. Nevertheless, the informative content of the uncertainty indexes turns out to be relevant during periods of market distress, when the role of oil risk is the predominant interest, with heterogeneous effects over the different quantiles levels.



## 1. Introduction

Following the seminal work of Hamilton [1], a large literature connects movements in oil returns and its volatility with recessions and inflationary episodes in the US economy (see, e.g., [2–4] and [5] for detailed reviews). Hamilton [6] indicates that nine out of ten recessions in the US since World War II have been preceded by an increase in oil prices. Interestingly, Hamilton [7] even goes as far as arguing that a large proportion of the recent downturn in the US GDP during the 'Great Recession' can also be attributed to the oil price shock in the period 2007–2008.

Commodity markets, just like asset prices, are known to be functions of the state of the economy [8]. In this regard, a recently growing literature emphasizes the role of economic policy uncertainty on business cycles (see, e.g., [9–13] and [14]

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for detailed reviews) which in turn affects oil-price movements (see, e.g., [3–5] and [15]). On the demand side, uncertainties can also drive economic concerns on the part of consumers, thus affecting the level of consumption growth in the economy. Therefore, considering the suggestion by Bernanke [16] that both oil and the stock markets tend to move together, as they both react to a common factor reflecting global aggregate demand, one obvious channel that links uncertainty to oil market movements is its potential effect on growth expectations for both output and consumption. Equity-market uncertainty also feeds into oil price movements because, as Bloom [9]'s firm-based theoretical framework notes, equity-market uncertainty affects hiring and investment and, hence, the production decisions of firms. In this regard, the empirical evidence relating to oil price movements and stock market volatility can be found in [3,4]. While these channels are likely to cause economic uncertainties to affect oil market movements at lower frequencies, high frequency (for example, daily) impacts can originate from other possible channels.

For instance, uncertainty can affect oil return dynamics via its contribution to jump risk in oil prices. There is growing evidence suggesting that jumps account for a large part of the variation in crude oil prices and that a substantial part of the risk premium in oil derivatives prices is due to jumps (see, e.g., [17,18] and [19]). Therefore, it could be argued that economic uncertainties contribute to the presence of jumps in oil prices, which in turn drive return and volatility dynamics in the oil market. Hence, even though the oil market is one of the most deep and liquid markets, complemented by a set of oil-related derivative instruments, if the jump risks emanating from economic policy and equity market uncertainties cannot be effectively hedged through the variety of available instruments, then these uncertainties are likely to influence the oil market. Alternatively, given that these uncertainties have been shown to affect equity markets (see, e.g., [20] for a detailed literature review in this regard), investors might in fact move funds to diversify their portfolios by investing in the commodity market, including in oil, in the hope of hedging portfolio risks [21]. These sudden movements of investments into the oil market could also impact on returns and the volatility of crude oil. As indicated by Ji and Guo [22,23], uncertainty tends to move the oil market through a behavioral channel as well, i.e., by affecting market participants' psychological expectations.

Against this backdrop, the objective of this paper is to analyze the role of recently developed news-based measures of economic policy uncertainty (EPU) and equity market uncertainty (EMU) by Baker et al. [24] in causing in the [25] sense and forecasting oil returns and their risk. Given the possibility that the oil market is also likely to drive these uncertainty measures – see, e.g., [3,4] and [5]–we employed a modified bivariate quantile causality-based model, as developed by Balcilar et al. [26,27,28]; notably, it combines the causality in quantile test of Jeong et al. [29] with the $k$th order nonparametric Granger causality test of Nishiyama et al. [30]. By resorting to this quantile-based analysis of causality, we evaluated the impact of news-based measures of uncertainty on both the returns and the risk of oil across a collection of quantiles. Testing for causality in risk allows us to shed some light on the volatility spillover phenomenon, since at times, the simple causality in returns series may not exist, but there may be significant relationships at higher moments. Notably, using quantile-based methods allows us to analyze the causality structure depending on the volatility state (high versus low).

Balcilar et al. [26] developed the framework we employed in this study to analyze the causality relationships running from EPU and EMU to oil returns and risk. They concluded that, for oil returns, EPU and EMU have strong predictive power over the entire distribution, barring the regions around the median, but for risk the predictability virtually covers the entire distribution, with some exceptions in the tails.[1] We extend the paper by Balcilar et al. [26] in various important ways. First, we made use of a rolling window procedure, by which we provided a time-varying approach to the in-sample quantile causality for both oil returns and risk. This is important, given that we detected structural breaks in the estimated conditional distributions over time; therefore, the full-sample quantile causality, as in [26], could possibly be misleading. Indeed, in contrast to [26], the empirical findings arising from the rolling window analysis suggest that EPU and EMU are not always relevant drivers in causing and forecasting the conditional quantiles of oil returns and risk, but are only so during particular periods, especially ones of market distress. Furthermore, our results show evidence of stronger relationships between the two uncertainty indexes and oil risk, with respect to oil returns. This important finding is consistent with the fact that EPU and EMU are uncertainty indexes and, therefore, are directly connected to oil risk, quantified by its volatility, which itself is a measure of dispersion, or uncertainty.

Second, starting with [26–28], in which causality in risk is implemented by using squared returns, we went further by directly considering the realized volatility of oil. We found that the two approaches provide similar implications at central quantiles levels, but differ for the extreme quantiles, thus challenging the use of squared oil returns for the analyses of volatility causation between oil and uncertainty measures.

Finally, we accompanied the causality exercise with a forecasting analysis. In contrast to [8], where the authors focus only on a point forecast of oil returns, we were able to analyze the density forecast for both oil returns and risk. In particular, we made use of the causality detected in designing the quantile regression models [31], and in doing that we adjusted the original estimated quantiles to guarantee their coherence; that is, their increasing monotonicity in $\tau \in (0, 1)$. Indeed, the approach introduced by Koenker and Bassett [31] allows the estimation of the single quantiles individually. As a consequence, when the analysis focuses on many quantiles, they may cross each other at specific quantile levels. Then, from a large collection of corrected quantiles, we built the conditional density of oil returns and risk through a non-parametric kernel-based method. This again is more informative than the point forecasts, since we were able to understand the role of EPU and EMU in forecasting oil movements in different phases (bearish, normal and bullish) of the market. Moreover, extending the analysis to the entire conditional distribution is of relevant importance in evaluating the uncertainty associated with the single point

[1] Note that Balcilar et al. [26] focus just on the in-sample analysis. In contrast, we provide here an extensive analysis both in-sample and out-of-sample.