Evaluating tail risks for the US economic policy uncertainty

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**Abstract**

The goal of this paper is to employ a relatively new methodological approach to extract quantile-based economic policy uncertainty risk forecasts using the Quantile Autoregressive Distributed Lag Mixed-Frequency Data Sampling (QADL-MIDAS) regression model recommended by Ghysels and Iania (2018). This type of modelling delivers better quantile forecasts at various forecasting horizons. The forecasting results not only imply that the risk measure of economic policy uncertainty measure is linked to the future evolution of the index itself, but also it help constructing explicitly EPU risk measures, which are used to identify what drives such risk policy measures, especially across certain sub-sample periods associated with major global events, such as the collapse of the Lehman Brothers, the Trump’s election, and the trade-war tensions between the US and China. The findings offer a new empirical perspective to the existing economic policy uncertainty literature, documenting that special world events carry a strong informational content as being a primary key to understand the dynamics of the economic policy tails.

**KEYWORDS**: economic policy uncertainty; risk; QADL-MIDAS model

**JEL CLASSIFICATION**: E61; C21; C53; C54

**1 INTRODUCTION**

Uncertainty refers to clarity, or lack thereof, about future economic activity. It incorporates both ‘risk’ and ‘Knightian uncertainty’. In the former, the probabilities of potential outcomes are known, but which outcome will occur is not. In the latter, neither the probabilities of outcomes, nor the eventual outcome are known (Cagliarini and Heath, 2000). In practice, the two are difficult to disentangle, so the analysis will be referring to a single concept of uncertainty that blends both throughout the entire paper. In the wake of the 2008 global financial crisis and the growing partisan policy disputes in the US, there are increasing and growing concerns about uncertain policies primarily related to economic policies and financial decisions (Baker et al., 2016), while policy uncertainties have always played a critical role in shaping economic outcomes, as evidenced by sluggish economic growth events in many countries that are currently experiencing policy uncertainties. In addition, uncertainty has been frequently quoted as a fundamental reason for the weak global recovery from the financial crisis (Moore, 2017).

Economic policy uncertainty (EPU) is the economic risk associated with undefined future government policies and regulatory frameworks. This further increases the risk that both businesses and individuals will delay their spending and investments due to market uncertainty. According to Baker et al. (2016), after the 2008 global financial crisis, uncertainty around government policies peaked due to business and household uncertainty regarding the government’s future regulatory framework, spending, taxes, monetary policies, and healthcare. They suggest that policy uncertainty particularly delayed the possibility of recovery from the recession as businesses and households postponed their decisions about investment and consumption expenditures. EPU has a crucial impact on the spending and investments of governments, businesses, and households, which motivates researchers to identify uncertainty measures, especially in relation to uncertainty in economic policies, which has resulted in several proxies for uncertainty.

The literature has recommended certain different measures of economic uncertainty to assess its effects on various segments in the economy. Based on the work by Bloom (2014) and Kozeniauskas et al. (2018), the proxies of uncertainty are organized into three groups: i) measures of uncertainty about macroeconomic outcomes (macro uncertainty), ii) measures of the dispersion of firm outcomes (micro uncertainty), iii) and measures of the uncertainty that people have about what others believe, which usually arises when forecasts differ (higher-order uncertainty). To the empirical ends of this paper, we focus on the first group. More specifically, the literature proposes four distinct proxies of macro uncertainty, including financial uncertainty, a volatility process for the macro variables, economic policy uncertainty, and Jurado, Ludvigson, and Ng (JLN) uncertainty.

The first type of macro uncertainty is financial uncertainty, which is measured by the realized or implied volatility of the stock market. The US VIX index is a popularly used proxy of US uncertainty and global financial uncertainty given the dominant role of the US in the global economy (Popp and Zhang, 2016; Choi, 2017, 2018; Bhattarai et al., 2019). The implied volatility is calculated as a weighted average of the price of put and call options and is intended to generate a portfolio of options that isolates the expected volatility of the S&P500 index at the 30-day. Formally, the option-implied volatility is defined as the risk-neutral expectation of the volatility of the S&P 500 index over the next 30 days. Compared to the US, implied volatility in most countries (especially emerging economies) is often available for a much shorter period, which prevents a meaningful time-series analysis (Choi and Shim, 2019). The realized volatility is an alternative of implied volatility. As a nonparametric alternative, realized volatility is flexible and feasible in multivariate applications and easy to implement. The second type of macro uncertainty is estimating a volatility process of macroeconomic variables, such as a stochastic volatility model and a GARCH model. GARCH-based models generally fail to capture the magnitude of sudden volatility increases compared to the stochastic volatility model and realized volatility (Cascaldi-Garcia et al., 2020). The third type of macro uncertainty is economic policy uncertainty (EPU) constructed by counting occurrences of events related to uncertainty (Baker et al., 2016). The idea of counting words related to uncertainty in newspaper articles has proven to be particularly popular, because it is easy to do with modern statistical packages and search engines, and it can be combined with natural language processing (Fernández-Villaverde and Guerrón-Quintana, 2020). The final type of macro uncertainty is proposed by Jurado et al. (2015), which is known as JLN uncertainty in reference to those authors’ names. The JLN uncertainty is estimated based on the implied forecast errors for real economic activity derived from a factor model that utilizes hundreds of economic and financial series.

EPU also appears to vary strongly over time, rising sharply in recessions and falling in booms (Campbell et al., 2001; Alexopoulos and Cohen, 2009; Fajgelbaum et al., 2012; Orlik and Veldkamp, 2012). It also varies heavily across countries, with developing countries appearing to have about a third more macro uncertainty than developed countries (Koren and Tenereyo, 2007). Furthermore, two mechanisms appear to drive changes in EPU over time, the types of exogenous shocks that often cause recessions, such as wars, oil price jumps and financial panics, and it endogenously rises further during recessions, as economic slowdowns increase micro and macro volatility. The evidence suggests uncertainty is damaging for short-run growth, reducing firms’ willingness to hire and invest, and consumers’ willingness to spend. By contrast, there is also some evidence that uncertainty can stimulate R&D, i.e. faced with a more uncertain future some firms appear more willing to innovate. Although following the 2008 crisis, economic uncertainty appears to have waned, US EPU remains high due to the ongoing fiscal debates, potentially slowing the recovery.

However, what this extensive literature has not explored so far is the role of potential tail risks associated with the EPU measure. Although this uncertainty measure unveils the role of several economic and non-economic events, potentially some of them carry different (asymmetric) risks, an aspect of the EPU measures overlooked by the literature. In the presence of tail risks, the conditional economic policy uncertainty mean does not necessarily adequately represent the EPU outlook. The literature needs to provide evidence that the response of the tails and the mean of the EPU distribution reveals a more complete picture of these effects, as well as to identify potential drivers that move the EPU distribution.

Therefore, the goal of this paper is to find out what conclusions can be drawn from a closer look at the entire conditional EPU distribution, using data from the US. To this end, the analysis makes use of the Quantile Autoregressive Distributed Lag Mixed-Frequency Data Sampling (QADL-MIDAS) regression model, recommended by Ghysels and Iania (2018) in forecasting economic uncertainty quantiles, while it can also extract model-implied risk measures for economic uncertainty. This research contributes to the literature on modeling economic uncertainty risks in showing that this model offers better forecasts in terms of out-of-sample forecasts in conditional quantiles. Moreover, it is used to construct economic policy uncertainty risk measures that at a later stage of the analysis can identify not only potential drivers of the EPU distribution, but also to explore how these drivers behave across certain periods associated with global economic and non-economic events.

This work is associated with two strands of literature. First, it extends the Quantile MIDAS (Q-MIDAS) model to allow for an autoregressive term, which is essential when the response variable is highly persistent. Q-MIDAS and QADL-MIDAS models efficiently relate low-frequency data with high-frequency data by parameterizing regression using lag polynomial functions. Ghysels (2014) and Ghysels et al. (2016) introduce Q-MIDAS regressions to model equity returns and their higher-order moments, i.e. conditional skewness. This model is also an extension of the QADL model introduced by Galvao et al. (2013) that accounts for high-frequency information. This paper uses the proposed quantile regression model to extract economic uncertainty risk measures and analyze the impact of these risks on future economic uncertainty realizations.

The analysis uses certain proxies for economic uncertainty, such as newspaper-based measures of uncertainty, like those offered by Baker et al. (2016), finance-based measures, such as stock market volatility, and measures of disagreement among forecasters for key economic variables. The findings illustrate that the proposed method outperforms a standard QAR benchmark model in fitting and forecasting conditional quantiles of economic uncertainty. The model performs better in terms of out-of-sample forecasting and also shows that economic uncertainty risk measures extracted are significant predictors of future economic uncertainty, which behave asymmetrically across certain sub-periods associated with major global economic and non-economic events.

The paper is organized as follows. First, in Section 2, it introduces the methods. Section 3 discusses the data employed to serve the ends of the empirical analysis, while it highlights the out-of-sample results in Section 4. Finally, in Section 5, it concludes and discusses the implications of forecasting future economic uncertainty realizations.

**2 METHODOLOGY**

The analysis is based on a new conditional quantile regression model, the Quantile Auto-Regressive Mixed-Frequency Data Sampling (QADL-MIDAS) regression model, recommended by Ghysels and Iania (2018). This methodology extracts risk measures by using regression quantiles, which directly model h-step ahead EPU. Standard conditional volatility models seem to suffer when they come to forecast multiple horizons due to temporal aggregation issues, as discussed in Ghysels (2014) (The Appendix offers more technical details on this new methodology).

To extract EPU risk measures, the method models the τ-th quantile of h-step ahead EPU series (EPU(h)t+h) based on all the available information at time t. Ft+h|t(EPU(h)) = P(EPU(h)t+h < EPU|Ft) is the (conditional) cumulative distribution function (CDF) of EPU (Ft is the information available at time t). The conditional quantile τ of h-step ahead EPU is EPU(h)t+h is:

qτ,t+h(EPU(h)t+h) = F−1t+h|t (EPU(h)) (1)

The reference model is the Quantile Auto-Regression (QAR) model recommended by Koenker and Xiao (2006). The analysis extends this model to that recommended by Ghysels and Iania (2018), i.e. the QADL-MIDAS model where the regression quantiles depend on the past values of EPU. Koenker and Xiao (2006) recommend the QAR model, where the auto-regression (AR) framework allows the coefficients to be quantile-level dependent. The analysis considers the AR(p) model for 1-step ahead prediction:

p-1 q-1

EPUt+1 = µ + Σ αjEPUt−j + εt+1 ≡ µ + ρEPUt + Σ βj∆EPUt−j + εt+1 (2)

j=0 j=0

where µ is the intercept and β = (β0, . . . , βp−1) is a vector of autoregressive coefficients. According to Manzan and Zerom (2015), the analysis considers ρ evolving as:

p-1

ρ = Σ αj , which shows the persistence of EPU, while q = p − 1 defines the lags.

j=0

If we need the AR coefficients to be quantile-level dependent, a QAR model is explicitly used as:

q-1

qτ(EPUt+1|Ft) = µτ + ρτEPUt + Σ βτ,j∆EPUt−j (3)

j=0

where τ∈(0, 1) is the quantile level, and the regression coefficients are quantile-dependent. Next, the analysis will provide forecasts for h-step ahead EPU quantiles; in this case, the QAR model yields:

q-1

qτ(EPU(h)t+h|Ft) = µτ + ρτEPUt + Σ βτ,j∆EPUt−j (4)

j=0

Equation (4) implies that the method regresses the information available at time t, on t-h, to forecast the t+h quantile. Quantiles cannot be easily temporally aggregated, which makes iterative forecasts not available (Ghysels, 2014) (direct versus iterative conditional mean forecasting of macroeconomic variables has been discussed by Marcellino et al. (2006) and Faust and Wright (2013)), with the direct approach performing better. In this modelling approach, the h-step ahead quantile of EPU depends on the current level and on an additional term (as in the case of the CAViaR model recommended by Engle and Manganelli, 2004):

qτ(EPU(h)t+h|Ft) = µτ + ρτEPUt + βτZt(θ) (5)

q-1

with Zt(θτ) = Σ ωm(θτ)|∆EṔUt−m|

m=0

The process also involves mixed-frequency data. The analysis employs a specification that avoids parameter proliferation as is typical in MIDAS regressions; therefore, it uses a specific form for the polynomial ωm through a normalized beta probability density function, while the weights are provided by:

q-1

ωm = (1 − xm)θ / Σ (1 − xm)θ (6)

m=0

where xm = (m−1)/(h−1). Given that ωm depends on a single parameter θ, the model is highly parsimonious, yet flexible enough to capture the potential dynamics of the EPU measure. According to Ghysels and Iania (2018), the model has several novelties: i) it uses a tightly parameterized polynomial, b) it avoids potential over-fitting problems even if it adds a large number of lags for the DL term, and iii) the parsimonious beta lag polynomial function ωm allows to specify the model at any sampling frequency. Since certain components of EPU are measured on a quarterly basis, this is potentially an important feature that allows researchers to model the feedback effects of EPU risks towards such components. The analysis estimates both QAR and QADL-MIDAS models by minimizing the usual check-loss function as it has been frequently recommended in the quantile regression literature (Koenker, 2005; Galvao et al., 2013).

**3 DATA**

The analysis makes uses of various measures of economic uncertainty: first, to capture uncertainty reflected in media coverage, it follows the Baker et al. (2016) measure of newspaper articles that reference economic uncertainty. The available time span runs from January 1985 to May 2020, with the data coming from: http://www.policyuncertainty.com. The idea behind this measure is that information about economic uncertainty could be contained in newspaper coverage, not that media coverage causes economic uncertainty. These newspaper-based measures have a number of benefits. They capture a broad range of uncertainty (unlike, for example, finance-based measures) and are extremely timely, the search can be run daily, although the analysis here uses monthly averages.

Moreover, the beauty and innovation of Baker et al.’s (2016) index is that most of the factors that affect economic policy uncertainty are summed up in one simple index, while it is publicly available and easy to use. The authors aggregate several factors into a new index, the economic policy uncertainty index (EPU), by using the average of three parts: the extent of newspaper coverage for policy-related economic uncertainty, how many provisions in the federal tax code expire soon, and the disagreement among economic forecasters. The authors assert that the coverage of policy-related economic uncertainty in reputed newspapers can aid in understanding the EPU indicators. This can be measured by searching for newspaper articles containing the words ‘economic’, ‘economy’, ‘uncertainty’, and ‘uncertain’, along with ‘regulation’ and ‘legislation’, and one or more of the following terms: ‘congress’, ‘legislation’, ‘white house’, ‘regulation’, ‘federal reserve’, or ‘deficit’.

Next, the analysis uses finance-based measures. Stock market volatility is a commonly used proxy for uncertainty, because it is available in real time and is reasonably comparable across countries. Caggiano et al. (2014) use it to assess the effects of uncertainty on the US economy, Bekaert et al. (2013) decompose it into a risk aversion component and an uncertainty component to test how monetary policy affects both, and Baker and Bloom (2013) use natural disasters and stock market volatility to assess the effects of uncertainty. Given that financial uncertainty is necessarily about the future, forward-looking measures of stock volatility are conceptually preferable. A measure of forward-looking stock market volatility can be represented by the VIX index (Bekaert et al., 2013); data are on a daily basis, are obtained from the Federal Reserve Bank of St. Louis, and span the period January 1, 1990 to June 25, 2020.

Finally, the third type of economic uncertainty measures comes from forecasters’ disagreement (Bachmann et al., 2010). Measures of dispersion between forecasters for economic variables can also proxy for economic uncertainty. Heightened economic uncertainty widens the potential distribution of outcomes, and this should show up as greater dispersion among forecasters. However, an important criticism of measures of forecast dispersion is that forecast dispersion and uncertainty are not identical. Forecast dispersion might instead capture disagreement, i.e. how far forecasters are from one another, not uncertainty. Each forecaster could be extremely certain, but there could still be a high degree of disagreement (and vice versa). Some authors have argued that, in light of this distinction, forecast dispersion is a poor proxy for uncertainty (Rich et al., 2012). In contrast, forecast dispersion measures are closely conceptually connected to economic activity. Data come from the Survey of Professional Forecasters (SPF) from the Philadelphia Federal Reserve Bank. The SPF asks professional forecasters to give their forecast for 32 key macroeconomic variables, including gross domestic product (GDP), short- and long-term inflation, and unemployment. The data use a measure of dispersion, such as variance. Data are on a quarterly basis and span the period 1990:1-2020:2 (Data sets on SPF variable forecast dispersion are available at: <http://www.philadelphiafed.org/research-and-data/realtime-center/spf-forecast-dispersion.cfm>.).

**4 EMPIRICAL ANALYSIS**

**4.1 Estimates of the QAR and QADL-MIDAS models**

For the ends of the empirical analysis, we consider quantile levels (0.05, 0.25, 0.5, 0.75 and 0.95) for the 12-month ahead US EPU index series. The analysis starts with the QAR model, which is estimated using maximum 12 lags. The estimates, reported in Table 1, illustrate that the EPU persistence is heterogeneous across the quantiles, with the evidence remaining consistently similar across all three definitions of EPU. The estimates also display that the persistence parameter ρ increases in quantiles, indicating that the lower-tail quantiles are less persistent than those of the upper tail. The results seem stronger in the case of the traditional EPU news measure.

**TABLE 1** Parameter estimates of the QAR model: EPU

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

Quantiles 0.05 0.25 0.50 0.75 0.95

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

**EPU news**

μ -0.413\*\* 0.672\*\*\* 0.985\*\*\* 1.674\*\*\* 2.663\*\*\*

[0.04] [0.00] [0.00] [0.00] [0.00]

ρ 0.569\*\*\* 0.712\*\*\* 0.952\*\*\* 1.327\*\*\* 1.895\*\*\*

[0.00] [0.00] [0.00] [0.00] [0.00]

Statistic [0.89] [0.94] [0.98] [0.93] [0.99]

**Financial EPU**

μ -0.365\*\* 0.601\*\*\* 0.892\*\*\* 1.248\*\*\* 2.295\*\*\*

[0.05] [0.00] [0.00] [0.00] [0.00]

ρ 0.491\*\*\* 0.629\*\*\* 0.861\*\*\* 1.075\*\*\* 1.438\*\*\*

[0.01] [0.00] [0.00] [0.00] [0.00]

Statistic [0.85] [0.91] [0.96] [0.89] [0.97]

**Dispersion of SPF**

μ -0.344\*\* 0.589\*\*\* 0.851\*\*\* 1.137\*\*\* 2.056\*\*\*

[0.05] [0.00] [0.00] [0.00] [0.00]

ρ 0.458\*\*\* 0.594\*\*\* 0.825\*\*\* 1.003\*\*\* 1.286\*\*\*

[0.01] [0.00] [0.00] [0.00] [0.00]

Statistic [0.87] [0.90] [0.94] [0.86] [0.95]

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

*Note*. The standard errors are based on a wild bootstrap tailored for quantile regression (Feng et al., 2011), while 1,000 bootstrap replications were used. Figures in brackets denote p-values. \*\*: p≤0.05; \*\*\*: p≤0.01.

The second step of the empirical analysis reports the estimates of the QADL-MIDAS model. The new findings are presented in Table 2. The model is estimated using one lag of past EPU and 12 lags for absolute (past) EPU’s changes. This lag pattern is maintained for the three alternative definitions of EPU. The slope coefficient of the (weighted) absolute deviations’ term, which is highly significant for most quantiles, indicates large conditional asymmetry in EPU. The estimates highlight that the sign of β coefficients is negative (positive) for lower (higher) quantiles, implying that periods of (absolute) large changes in EPU amplify extreme realizations, i.e. in periods of low (high) levels of EPU, higher EPU variability triggers even lower (higher) EPU realization. Additionally, the persistence coefficient seems to be higher for the QADL-MIDAS specification relative to that of the QAR. The above observations stand similar for the three alternative definitions of EPU.

**TABLE 2** Parameter estimates of the QADL-MIDAS model

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

Quantiles 0.05 0.25 0.50 0.75 0.95

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

**EPU news**

μ 0.104 0.329\*\* 0.759\*\*\* 1.369\*\*\* 1.938\*\*\*

[0.36] [0.02] [0.00] [0.00] [0.00]

β -0.674\*\*\* -0.187 1.253\*\*\* 1.874\*\*\* 2.319\*\*\*

[0.00] [0.19] [0.00] [0.00] [0.00]

θ 27.092 22.308 12.138 2.351 0.975

[0.37] [0.44] [0.62] [0.78] [0.81]

ρ 0.501\*\*\* 0.784\*\*\* 0.961\*\*\* 1.328\*\*\* 2.017\*\*\*

[0.00] [0.00] [0.00] [0.00] [0.00]

Statistic [0.90] [0.87] [0.96] [0.92] [0.98]

**Financial EPU**

μ 0.088 0.302\*\* 0.596\*\*\* 1.184\*\*\* 1.549\*\*\*

[0.43] [0.03] [0.00] [0.00] [0.00]

β -0.581\*\*\* -0.142 1.136\*\*\* 1.389\*\*\* 2.074\*\*\*

[0.00] [0.27] [0.00] [0.00] [0.00]

θ 24.873 17.842 9.342 1.816 0.746

[0.43] [0.56] [0.68] [0.82] [0.85]

ρ 0.428\*\*\* 0.642\*\*\* 0.804\*\*\* 1.093\*\*\* 1.754\*\*\*

[0.01] [0.00] [0.00] [0.00] [0.00]

Statistic [0.86] [0.82] [0.90] [0.85] [0.93]

**Dispersion of SPF**

μ 0.064 0.268\*\* 0.537\*\*\* 1.025\*\*\* 1.382\*\*\*

[0.51] [0.05] [0.00] [0.00] [0.00]

β -0.526\*\*\* -0.127 1.044\*\*\* 1.216\*\*\* 1.648\*\*\*

[0.00] [0.35] [0.00] [0.00] [0.00]

θ 20.316 13.238 5.139 1.225 0.513

[0.49] [0.61] [0.74] [0.87] [0.90]

ρ 0.379\*\* 0.539\*\*\* 0.682\*\*\* 0.946\*\*\* 1.273\*\*\*

[0.02] [0.00] [0.00] [0.00] [0.00]

Statistic [0.83] [0.80] [0.87] [0.82] [0.89]

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

*Note*. The standard errors are computed using a wild bootstrap tailored for quantile regression (Feng et al., 2011), while 500 bootstrap replications were used. Figures in brackets denote p-values. \*\*: p≤0.05; \*\*\*: p≤0.01.

Overall, the results indicate that the dependence in EPU is a quantile-specific process, with the QADL-MIDAS modelling process stressing the fact that the impact of changes of past EPU on the EPU’s distribution is quantile-dependent.

**4.2 Forecasting performance of the QAR and QADL-MIDAS models**

Next, the analysis assesses the out-of-sample forecasting performance of QADL-MIDAS against the benchmark QAR model. The primary focus is to evaluate how models perform in forecasting the tails of the EPU distribution. Using the QADL-MIDAS model, the h-step ahead quantile regression takes the following form:

qτ (π(h)t) = µτ + ρτ EPUt−h + βτZt−h(θ) (7)

with

q-1

Zt−h(θτ) = Σ ωm(θτ)|∆EṔUt−h−m|

m=0

where q is the number of lags of the changes in EPU, where EṔU and EPU(h)t are the monthly and h-period ahead EPU, respectively. For both models, the analysis uses 12 lags for 12-step ahead and 3 lags for 3-step ahead forecasting, respectively. To compute the h-step ahead forecast, the method estimates the model parameters by off-setting the right-hand-side (RHS) variables h-steps back. The forecast is computed as:

𝓆τ (π(h)t+h|t) = ϻτ + ῤτEPUt + ẞτ Zt(ˆθ) (8)

The analysis employs an expanding window forecasting scheme using (monthly) data, spanning the period January 1985 to May 2020. The initial in-sample period ranges from January 1985 to January 1995, and the first conditional quantile forecast is for January 1996, when it forecasts 12 months ahead, and April 1985, in the case of 3-month ahead prediction. The predictions are obtained as follows: i) we add the February 1985 data point to the training sample, ii) we estimate both models for both horizons, and iii) we compute the forecasts based on these estimates. The procedure is repeated until May 2020, which is the last out-of-sample forecasting date.

The method compares the forecasting results of QADL-MIDAS with the benchmark QAR model using the Clark and West (2007) and Yan and Tae-Hwy (2014) testing procedure for nested time series models:

ḟ(m) t+h|t = ǫτ (EPU(h)t+h|t)

is the conditional quantile forecast. The h-step ahead forecast errors are defined as:

ê(m)t+h|t = EPU(h)t+h − ḟ(m)t+h|t (9)

Next, the quantile check-loss function k(.) evaluated at the forecast error ê(m)t+h|t yields:

k(ê(m)t+h|t) = h(ê(m)t+h|t) ê(m)t+h|t (10)

where h(ê(m)t+h|t) = (τ − I(ê(m)t+h|t < 0)) is the tick function. According to Yan and Tae-Hwy (2014), it computes the (adjusted) sequence of check-loss-differential values:

ĉwt+h = g(êQARt+h|t) (êQARt+h|t − êQADL-MIDASt+h|t) (11)

and yields the CW-statistic:

CW = ćw / √Var(ćw) (12)

where,

T

ćw = 1/Tos Σ ĉwt+h

t=Tis+1

with Var(ćw) being the HAC-adjusted sample variance. Tis is the initial sample size, and Tos is the out-of-sample size, with T = Tis + Tos. Through the CW statistic, the analysis investigates the significance of any better forecasting performance relative to the benchmark. The null hypothesis is that both the benchmark and the QADL-MIDAS models have the same mean-forecast error. Finally, we compute the ratio of the average quantile check-loss at each quantile forecast:

T

ḱ(m) = 1/Tos Σ g(ê(m)t+h|t) (13)

t=Tis+1

for both models. The analysis defines the ratio of the average quantile check-losses as:

ratio = ḱQADL-MIDAS / ḱQAR (14)

A ratio smaller than one implies that the model performs better.

Tables 3 reports the out-of-sample results for all three alternative definitions of EPU for 12-month and 3-month horizons, respectively. The results are similar across all three alternative definitions of EPU. They also provide the average CW-statistic, the p-values of the test, the ratio and the performance outcome. In the case of the EPU news index, the findings highlight that the QADL-MIDAS model outperforms the QAR for longer horizons and mostly in the tails. For instance, at the 0.25 quantile level, the 12-month ahead forecasts are better compared to the benchmark. As it can be seen from the two tables, the improvement in performance is as high as 66%, 63% and 62% (at the 0.95 quantile for 12-month ahead). The results remain consistently similar across all three alternative definitions of EPU, although the best ratios are associated with the variable measured as EPU news. Similar results are obtained for the case of the 3-month ahead forecasts. Overall, the results clearly indicate that the forecasting performance get stronger at the high tails of the distribution, indicating that the new quantile risk measure contains more information about the economic uncertainty dynamics in relevance to high values of uncertainties.

**TABLE 3** Quantile out-of-sample forecasts (12-month ahead forecasts)

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

Quantiles 0.05 0.25 0.50 0.75 0.95

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

**EPU news**

CW statistic 2.137\*\* 1.563\* 2.639\*\* 3.551\*\*\* 3.908\*\*\*

[0.04] [0.07] [0.03] [0.00] [0.00]

ratio 0.718 0.785 0.594 0.415 0.337

Improvement 28% 21% 41% 58% 66%

**Financial EPU**

CW statistic 1.974\*\* 1.362\* 2.294\*\* 2.845\*\*\* 3.276\*\*\*

[0.05] [0.08] [0.04] [0.01] [0.00]

ratio 0.769 0.816 0.642 0.473 0.368

Improvement 23% 18% 36% 53% 63%

**Dispersion of SPF**

CW statistic 1.766\*\* 1.125\* 2.035\*\* 2.497\*\*\* 3.009\*\*\*

[0.05] [0.09] [0.05] [0.01] [0.00]

ratio 0.786 0.839 0.665 0.497 0.383

Improvement 21% 16% 33% 50% 62%

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*Note*. The conditional quantile forecasts are evaluated using one-sided Clark and West (2007) adjustment for nested models for quantile regression models as proposed by Yan and Tae-Hwy (2014). CW statistics are adjusted using HAC Newey-West procedure. levels. p-values are in brackets. \*: p≤0.10; \*\*: p≤0.05; \*\*\*: p≤0.01.

**TABLE 4** Quantile out-of-sample forecasts (3-month ahead forecasts)

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

Quantiles 0.05 0.25 0.50 0.75 0.95

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

**EPU news**

CW statistic 0.229 1.354\* 2.952\*\*\* 3.479\*\*\* 3.962\*\*\*

[0.25] [0.06] [0.00] [0.00] [0.00]

ratio 1.352 0.844 0.538 0.459 0.381

Improvement (35%) 16% 46% 54% 62%

**Financial EPU**

CW statistic 0.168 1.085\* 2.346\*\* 3.059\*\*\* 3.368\*\*\*

[0.34] [0.08] [0.03] [0.01] [0.00]

ratio 1.531 0.895 0.677 0.502 0.419

Improvement (53%) 10% 32% 50% 58%

**Dispersion of SPF**

CW statistic 0.139 0.953\* 2.011\*\* 2.752\*\* 2.984\*\*\*

[0.38] [0.10] [0.05] [0.02] [0.01]

ratio 1.658 0.924 0.696 0.541 0.468

Improvement (66%) 8% 30% 46% 53%

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

*Note*. The conditional quantile forecasts are evaluated using one-sided Clark and West (2007) adjustment for nested models for quantile regression models as proposed by Yan and Tae-Hwy (2014). CW statistics are adjusted using HAC Newey-West procedure. levels. p-values are in brackets. \*: p≤0.10; \*\*: p≤0.05; \*\*\*: p≤0.01.

**4.3 Building EPU risk measures**

In the next step, the analysis analyzes EPU risk measures based on regression quantiles estimated using the QADL-MIDAS model. According to Andrade et al. (2012), it computes three different risk measures of EPU: i) the EPU-at-risk (EPUaR), ii) the inter-quantile range (EPUQR), and iii) the robust asymmetry measure (ASY). The EPUaR measure is given by the estimated quantile at the τ level, given information up to t-h:

EPUaRτt|t−h = 𝓆τ,t|t−h (15)

The measure is close to the well-known financial risk measure called ‘Value-at-Risk’ (VaR). According to Andrade et al. (2012), this measure considers the probability of extreme EPU realizations and, thus, provides information on the risk of high extreme EPU or low extreme EPU, i.e. the probability that EPU falls above or below a certain threshold. These risks are two-sided, with upside risks coming from ‘excessive economic policy uncertainty’ and downside risks from too low or even negative economic policy uncertainty. Next, the EPUQR is computed through the difference between the upper- and lower-tail quantiles at the τ level:

EPUQRτt|t−h = 𝓆1−τ,t|t−h − 𝓆τ,t|t−h (16)

This is a robust measure of uncertainty risk based on quantiles. As the EPUQR increases, extreme EPU realizations are more likely to occur.

Finally, the third metric of EPU risk measures the (a)symmetry of the distribution of future EPU’s realizations. This measure (ASY) comes as the deviation of the upper- and lower-tail regression quantiles from the median, standardized by the EPUQR. At the τ level, it is defined as:

ASYτt|t−h = [(𝓆1−τ,t|t−h − 𝓆0.50,t|t−h) − (𝓆0.50,t|t−h − 𝓆τ,t|t−h)] / [𝓆1−τ,t|t−h − 𝓆τ,t|t−h] (17)

Equation (17) implies that for any τ, the numerator measures the degree to which the distance of the 1-τ quantile from the median differs from the distance between the median and the τ quantile. In the case of a symmetric distribution, the two distances are similar and ASYτt|t−h = 0; in contrast, when (𝓆1−τ,t|t−h − 𝓆0.50,t|t−h) is larger (smaller) than (𝓆0.50,t|t−h − 𝓆τ,t|t−h), the distribution is skewed to the right (left).

Figure 1 plots the pattern of the ASY75t|t−h (at the 75th quantile) measure implied by the QADL-MIDAS model. A casual inspection of this measure allows us to infer that although many economic, political and geopolitical events occurred throughout the period under study that may have affected the presence of many spikes in the original absolute time series (such as presidential elections, Gulf Wars I and II, the 9/11 attacks, the European sovereign debt crisis, and major fiscal policy battles from 2011 to 2013), ASY75t|t−h is characterized by three main spikes (extreme risk): the September 2008 collapse of the Lehman Brothers bank, the reaction to the Donald Trump’s surprise election victory in November 2016, and escalating trade policy tensions between the US and China in 2018-2019. Before 2008, the distribution of EPU reflects that from 1985 until 2008, the model-implied likelihood of an increase in EPU (above the median value) was smaller than the risk of a decrease. In contrast, after 2008, the metric turns more volatile and it is, on average, positive, supporting a substantial asymmetric behavior.

**FIGURE 1** Estimated conditional asymmetry of year-on-year EPU index

Moreover, Figure 2 plots the three constructed economic policy uncertainty indexes through the QADL-MIDAS model. The picture clearly illustrates that all three new indexes indicate higher turbulence across time, while they seem to indicate higher uncertainty associated with the role of the pandemic (Covid-19) crisis over the time span January 2020-May 2020, coincided with the peak of the first wave of the pandemic crisis event, highlighting the stronger information content of the crisis for the size of economic policy uncertainty.



**FIGURE 2** Estimated conditional policy uncertainty indexes versus the EPU index

**4.4 Identifying potential drivers of the EPU risk measure**

Next, the analysis determines the determinants that affect the predictive EPU risk distribution. Jiang et al. (2019) identify a set of factors that affect the time series of the US economic policy uncertainty index. According to their analysis, they consider certain behavioral and macroeconomic forces, i.e. US Sentiment (measured through the Michigan Consumer Sentiment Index obtained from the Federal Reserve Bank of St. Louis), US trade deficit, US trade share, inflation, exchange rate, and the Dow Jones Industrial Average Index. Data are obtained from the Datastream database over the same time span. The analysis frames the effects of those different drivers on different EPU risk distribution quantiles.

First, the analysis considers the entire sample period (1985-2020) and the results are based on the quantile ARDL (QARDL) model for which detailed discussion can be found in Cho et al. (2015). The equation that describes our modelling approach is given below:

k k k

EPUriskt = δ0(τ) + Σδ1i(τ)EPUriskt-i + Σδ2i(τ) SENTt-i + Σδ3i(τ) TRDEFt-i +

i=1 i=0 i=0

k k k k

Σδ4i(τ) TRSHt-i + Σδ1i(τ)INFt-i + Σδ2i(τ) EXt-i + Σδ3i(τ) DJt-i +

i=0 i=0 i=0 i=0

g(τ)[EPUriskt-1 – β1(τ) SENTt-1 - β2(τ) TRDEFt-1 - β3(τ) TRSHt-1 - β4(τ) INFt-1 -

β5(τ) EXt-1 - β6(τ) DJt-1] + ut(τ)

where SENT is the sentiment index, TRDEF denotes the trade deficit, TRSH is the country’s trade share, INF is inflation (based on the CPI index), EX is the exchange rate (the country’s efficient rate), and DJ is the Dow-Jones Average stock market index. u is the error term, g(τ) is the error correction term, while the βs indicate long-run coefficients, the δs represent parameters for short-run dynamics, with τ∈(0,1) being a quantile index, and k is the lag order. According to Cho et al. (2012), the QARDL estimators of both the long-run (cointegrating) parameters and the short-run dynamics are shown to follow normal distributions asymptotically.

By using the Akaike information criterion (AIC), the optimal lag orders provide support to the QARDL (1, 1, 1, 0, 0, 1) model for the case of the EPUaR risk measure for EPU, the QARDL (1, 1, 1, 0, 0, 0) model for the case of the EPUQR risk measure for EPU, and the QARDL (1, 1, 0, 0, 0, 1) model for the case of the ASY risk measure for EPU; the results, based on selective quantiles, are reported in Table 5. They clearly document that most of the estimated coefficients are statistically significant across the quantiles considered. In terms of the error-correction parameter (ECM), most of these terms are significant at 5%, except in the case of the 0.1 quantile. We can conclude that a cointegrating relationship exists between the three alternative definitions of the EPU risk and the associated drivers under the condition of particular quantiles.

The long-run coefficients between the EPU risk and the drivers of the sentiment index, the exchange rate and the DJ financial index are significant across all of the quantiles, but the size of the coefficients varies across different quantiles (the remaining controls are either statistically insignificant or have low statistical significance, e.g. at 10%). Moreover, with respect to the short-term dynamics, it is (again) the sentiment index, the exchange rate, and the DJ market index that have significant effects on the EPU risk throughout most of the quantiles, with the results remaining consistently similar across the three alternative definitions of the EPU, with the strongest and highly significant being associated with the EPU news version.

Moreover, all the long-run coefficients show a monotonically downward trend through the quantiles except for the coefficients of the trade deficit and inflation (built on the CPI index). For these variables, the trend is upward even starting from the first quantile. In terms of short-run dynamics, the findings are very alike with the long-run trends. Overall, the quantile results clearly confirm strong evidence of location asymmetries between lower and medium-to-higher quantiles for most of the parameters.

**TABLE 5** QARDL estimates (Full period: January 1985-May 2020)

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

Variables τ: 0.1 0.3 0.5 0.7 0.9

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

**Dependent variable: ΔEPUaR**

ΔEPUaR(-1) 0.379\*\*\* 0.356\*\*\* 0.331\*\*\* 0.310\*\*\* 0.294\*\*\*

[0.00] [0.00] [0.00] [0.00] [0.00]

ΔSENT -0.186\*\*\* -0.167\*\*\* -0.129\*\*\* -0.092\*\*\* -0.088\*\*

[0.00] [0.00] [0.00] [0.01] [0.02]

ΔSENT(-1) -0.099\*\*\* -0.081\*\* -0.065\*\* -0.051\*\* -0.047\*\* [0.01] [0.02] [0.03] [0.05] [0.05]

ΔTRDEF 0.041\* 0.049\* 0.063\* 0.080\*\* 0.093\*\*

[0.10] [0.09] [0.06] [0.04] [0.03]

ΔTRDEF(-1) 0.024 0.036 0.049\* 0.043\* 0.055\*

[0.13] [0.11] [0.10] [0.10] [0.08]

ΔTRSH -0.033 -0.038 -0.035 -0.039 -0.042\*

[0.18] [0.17] [0.18] [0.13] [0.10]

ΔTRSH(-1) -0.014 -0.017 -0.025 -0.021 -0.023

[0.25] [0.22] [0.18] [0.20] [0.19]

ΔINF 0.034 0.039 0.046 0.059\* 0.071\*

[0.17] [0.14] [0.11] [0.09] [0.07]

ΔEX -0.088\*\* -0.081\*\* -0.056\* -0.047\* -0.038

[0.04] [0.05] [0.08] [0.09] [0.12]

ΔDJ -0.081\*\* -0.097\*\*\* -0.112\*\*\* -0.106\*\*\* -0.126\*\*\*

[0.03] [0.01] [0.00] [0.00] [0.00]

ΔDJ(-1) 0.046\* 0.059\* 0.065\*\* 0.077\*\* 0.089\*\*

[0.07] [0.06] [0.05] [0.04] [0.02]

g(-1) 0.028 0.042\* 0.050\* 0.062\*\* 0.071\*\*

[0.15] [0.09] [0.07] [0.05] [0.04]

SENT(-1) -0.197\*\*\* -0.175\*\*\* -0.140\*\*\* -0.109\*\*\* -0.092\*\*

[0.00] [0.00] [0.00] [0.01] [0.02]

TRDEF(-1) 0.048\* 0.056\* 0.069\*\* 0.061\* 0.075\*\*

[0.08] [0.06] [0.05] [0.06] [0.04]

TRSH(-1) -0.039 -0.033 -0.038 -0.046\* -0.038

[0.15] [0.18] [0.15] [0.09] [0.15]

INF(-1) 0.039 0.031 0.038 0.046 0.040

[0.14] [0.17] [0.14] [0.11] [0.13]

EX(-1) -0.091\*\* -0.067\* -0.072\* -0.052\* -0.033

[0.05] [0.07] [0.06] [0.10] [0.13]

DJ(-1) -0.092\*\* -0.101\*\*\* -0.118\*\*\* -0.113\*\* -0.125\*\*\*

[0.02] [0.01] [0.00] [0.00] [0.00]

**Dependent variable: ΔEPUQR**

ΔEPUQR(-1) 0.351\*\*\* 0.329\*\*\* 0.316\*\*\* 0.304\*\*\* 0.285\*\*\*

[0.00] [0.00] [0.00] [0.00] [0.01]

ΔSENT -0.177\*\*\* -0.162\*\*\* -0.118\*\*\* -0.080\*\*\* -0.069\*\*

[0.00] [0.00] [0.00] [0.01] [0.03]

ΔSENT(-1) -0.082\*\*\* -0.066\*\* -0.050\*\* -0.038\* -0.025\* [0.01] [0.03] [0.03] [0.07] [0.09]

ΔTRDEF 0.036\* 0.044\* 0.057\* 0.072\* 0.079\*\*

[0.10] [0.10] [0.07] [0.06] [0.05]

ΔTRDEF(-1) 0.018 0.027 0.036 0.041\* 0.048\*

[0.19] [0.15] [0.12] [0.10] [0.09]

ΔTRSH -0.026 -0.031 -0.033 -0.036 -0.039

[0.23] [0.20] [0.19] [0.15] [0.13]

ΔTRSH(-1) -0.011 -0.015 -0.022 -0.017 -0.020

[0.29] [0.24] [0.28] [0.23] [0.29]

ΔINF 0.029 0.035 0.040 0.051\* 0.065\*

[0.20] [0.17] [0.14] [0.10] [0.08]

ΔEX -0.079\*\* -0.068\* -0.050\* -0.039\* -0.030

[0.05] [0.06] [0.08] [0.10] [0.15]

ΔDJ -0.076\*\* -0.091\*\*\* -0.102\*\*\* -0.104\*\*\* -0.117\*\*\*

[0.03] [0.01] [0.00] [0.00] [0.00]

g(-1) 0.024 0.037\* 0.046\* 0.057\* 0.065\*\*

[0.19] [0.10] [0.08] [0.06] [0.05]

SENT(-1) -0.173\*\*\* -0.153\*\*\* -0.132\*\*\* -0.101\*\*\* -0.081\*\*

[0.00] [0.00] [0.00] [0.01] [0.03]

TRDEF(-1) 0.042\* 0.050\* 0.064\* 0.055\* 0.068\*\*

[0.09] [0.07] [0.06] [0.08] [0.05]

TRSH(-1) -0.032 -0.027 -0.031 -0.037 -0.034

[0.19] [0.24] [0.19] [0.15] [0.18]

INF(-1) 0.032 0.027 0.034 0.040 0.034

[0.18] [0.21] [0.16] [0.13] [0.16]

EX(-1) -0.084\*\* -0.061\* -0.066\* -0.043\* -0.026

[0.05] [0.08] [0.07] [0.10] [0.15]

DJ(-1) -0.084\*\* -0.097\*\* -0.107\*\*\* -0.109\*\*\* -0.116\*\*\*

[0.03] [0.02] [0.01] [0.01] [0.00]

**Dependent variable: ΔASY**

ΔASY(-1) 0.356\*\*\* 0.334\*\*\* 0.320\*\*\* 0.311\*\*\* 0.290\*\*\*

[0.00] [0.00] [0.00] [0.00] [0.01]

ΔSENT -0.181\*\*\* -0.168\*\*\* -0.124\*\*\* -0.087\*\*\* -0.075\*\*

[0.00] [0.00] [0.00] [0.01] [0.02]

ΔSENT(-1) -0.086\*\*\* -0.071\*\* -0.054\*\* -0.043\* -0.029\* [0.01] [0.03] [0.03] [0.06] [0.08]

ΔTRDEF 0.040\* 0.048\* 0.063\* 0.077\* 0.083\*\*

[0.09] [0.10] [0.07] [0.06] [0.05]

ΔTRDEF(-1) 0.022 0.031 0.040 0.046\* 0.055\*

[0.17] [0.14] [0.11] [0.09] [0.07]

ΔTRSH -0.032 -0.033 -0.037 -0.040 -0.042

[0.20] [0.19] [0.16] [0.13] [0.12]

ΔINF 0.034 0.039 0.045 0.056\* 0.069\*

[0.17] [0.15] [0.11] [0.09] [0.07]

ΔEX -0.084\*\* -0.073\*\* -0.056\* -0.044\* -0.036

[0.04] [0.05] [0.06] [0.08] [0.11]

ΔDJ -0.080\*\* -0.097\*\*\* -0.109\*\*\* -0.106\*\*\* -0.128\*\*\*

[0.02] [0.01] [0.00] [0.00] [0.00]

ΔDJ(-1) -0.057\* -0.068\*\* -0.079\*\* -0.071\*\* -0.078\*\*

[0.06] [0.05] [0.04] [0.05] [0.04]

g(-1) 0.029 0.041\* 0.053\* 0.062\*\* 0.069\*\*

[0.16] [0.09] [0.07] [0.05] [0.04]

SENT(-1) -0.179\*\*\* -0.160\*\*\* -0.137\*\*\* -0.112\*\*\* -0.093\*\*

[0.00] [0.00] [0.00] [0.00] [0.02]

TRDEF(-1) 0.046\* 0.055\* 0.071\*\* 0.059\* 0.074\*\*

[0.08] [0.06] [0.05] [0.06] [0.04]

TRSH(-1) -0.036 -0.031 -0.035 -0.042 -0.037

[0.16] [0.22] [0.17] [0.13] [0.16]

INF(-1) 0.035 0.030 0.039 0.045 0.038

[0.17] [0.19] [0.13] [0.11] [0.16]

EX(-1) -0.089\*\* -0.067\* -0.072\* -0.049\* -0.030

[0.04] [0.07] [0.06] [0.09] [0.13]

DJ(-1) -0.092\*\* -0.103\*\*\* -0.115\*\*\* -0.113\*\*\* -0.122\*\*\*

[0.02] [0.01] [0.00] [0.00] [0.00]

No. of obs. 425

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

*Note*. Figures in brackets denote p-values. Δ denotes first differences, g is the error correction term. \*: p≤0.10; \*\*: p≤0.05; \*\*\*: p≤0.01.

Finally, we use the ASY measure of the EPU risk and evaluate its determinants across sub-periods. More specifically, the sub-periods considered are associated with the events depicted in Figure 1 above, i.e. the September 2008 collapse of Lehman Brothers, the reaction to the Donald Trump’s surprise election victory in November 2016, and escalating trade policy tensions between the US and China in 2018-2019. Therefore, the analysis considers the following periods: Prior to September 2008, October 2008 to November 2016, December 2016 to May 2020. The results, reported in Table 6, illustrate that the drivers identified in Table 5 are active only over the period followed the President Trump’s election, implying the presence of a turbulence period that exacerbated the risk profile of the EPU index. These results receive robust support from the other two policy uncertainty risk measures. The results are available upon request and receive empirical support from Kelly et al. (2016), Altig et al. (2019), Baker et al. (2019), and Caldara et al. (2019).

**TABLE 6** QARDL estimates (Sub-sample periods)

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

Variables τ: 0.1 0.3 0.5 0.7 0.9

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

**Dependent variable: ΔASY (January 1985-September 2008)-(1, 0, 0, 0, 0, 1)**

ΔASY(-1) 0.262\*\* 0.225\*\* 0.189\* 0.134\* 0.118\*

[0.03] [0.05] [0.07] [0.10] [0.10]

ΔSENT -0.094\*\* -0.057\* -0.032\* -0.015 -0.006

[0.01] [0.06] [0.10] [0.16] [0.31]

ΔSENT(-1) -0.037\* -0.022 -0.013 -0.006 -0.000 [0.09] [0.14] [0.20] [0.28] [0.39]

ΔTRDEF 0.019 0.035 0.046\* 0.053\* 0.049\*

[0.16] [0.12] [0.09] [0.07] [0.08]

ΔTRSH -0.018 -0.030 -0.039 -0.046 -0.041

[0.34] [0.24] [0.17] [0.12] [0.14]

ΔINF 0.039 0.043 0.049\* 0.058\* 0.071\*

[0.13] [0.11] [0.10] [0.08] [0.06]

ΔEX -0.052\* -0.060\*\* -0.067\*\* -0.064\*\* -0.054\*

[0.06] [0.05] [0.04] [0.05] [0.06]

ΔDJ -0.075\*\* -0.091\*\*\* -0.103\*\*\* -0.101\*\*\* -0.139\*\*\*

[0.02] [0.01] [0.00] [0.00] [0.00]

ΔDJ(-1) -0.053\* -0.064\*\* -0.075\*\* -0.069\*\* -0.082\*\*

[0.07] [0.05] [0.05] [0.05] [0.03]

g(-1) 0.025 0.036 0.048\* 0.051\* 0.057\*

[0.19] [0.11] [0.09] [0.09] [0.07]

SENT(-1) -0.136\*\*\* -0.118\*\*\* -0.094\*\* -0.073\*\* -0.060\*

[0.00] [0.01] [0.03] [0.05] [0.06]

TRDEF(-1) 0.034 0.038 0.035 0.043\* 0.048\*

[0.13] [0.11] [0.12] [0.09] [0.08]

TRSH(-1) -0.021 -0.027 -0.030 -0.032 -0.027

[0.29] [0.25] [0.22] [0.21] [0.25]

INF(-1) 0.019 0.023 0.029 0.024 0.031

[0.36] [0.31] [0.25] [0.28] [0.20]

EX(-1) -0.049\* -0.055\* -0.059\* -0.055\* -0.051\*

[0.07] [0.06] [0.06] [0.07] [0.08]

DJ(-1) -0.088\*\* -0.106\*\*\* -0.105\*\*\* -0.109\*\*\* -0.117\*\*\*

[0.02] [0.00] [0.00] [0.00] [0.00]

No. of obs. 285

**Dependent variable: ΔASY (October 2008-November 2016)-(1, 1, 0, 0, 0, 0)**

ΔASY(-1) 0.409\*\*\* 0.386\*\*\* 0.364\*\*\* 0.345\*\*\* 0.319\*\*\*

[0.00] [0.00] [0.00] [0.00] [0.00]

ΔSENT -0.246\*\*\* -0.224\*\*\* -0.197\*\*\* -0.176\*\*\* -0.148\*\*\*

[0.00] [0.00] [0.00] [0.00] [0.00]

ΔSENT(-1) -0.079\*\* -0.072\*\* -0.061\*\* -0.054\*\* -0.050\*\* [0.03] [0.03] [0.04] [0.05] [0.05]

ΔTRDEF 0.054\*\* 0.062\*\* 0.076\*\* 0.089\*\*\* 0.097\*\*\*

[0.04] [0.03] [0.02] [0.01] [0.01]

ΔTRDEF(-1) 0.028\* 0.033\* 0.036\* 0.042\* 0.049\*

[0.09] [0.08] [0.08] [0.06] [0.06]

ΔTRSH -0.030 -0.036 -0.042 -0.049\* -0.045

[0.17] [0.14] [0.11] [0.10] [0.11]

ΔINF 0.046\* 0.050\* 0.058\* 0.054\* 0.075\*\*

[0.10] [0.09] [0.09] [0.09] [0.05]

ΔEX -0.059\* -0.066\*\* -0.072\*\* -0.074\*\* -0.085\*\*

[0.06] [0.05] [0.04] [0.04] [0.02]

ΔDJ -0.088\*\* -0.097\*\*\* -0.112\*\*\* -0.124\*\*\* -0.142\*\*\*

[0.02] [0.01] [0.00] [0.00] [0.00]

ΔDJ(-1) -0.057\* -0.068\*\* -0.079\*\* -0.076\*\* -0.089\*\*

[0.07] [0.04] [0.04] [0.04] [0.02]

g(-1) 0.036 0.041\* 0.052\* 0.058\* 0.073\*\*

[0.12] [0.09] [0.07] [0.06] [0.03]

SENT(-1) -0.189\*\*\* -0.164\*\*\* -0.147\*\*\* -0.153\*\*\* -0.142\*\*\*

[0.00] [0.00] [0.00] [0.00] [0.00]

TRDEF(-1) 0.039 0.046\* 0.057\* 0.052\* 0.066\*\*

[0.12] [0.10] [0.08] [0.09] [0.05]

TRSH(-1) -0.027 -0.032 -0.036 -0.031 -0.029

[0.23] [0.20] [0.16] [0.20] [0.22]

INF(-1) 0.025 0.029 0.026 0.021 0.038

[0.31] [0.27] [0.22] [0.29] [0.13]

EX(-1) -0.063\*\* -0.069\*\* -0.075\*\* -0.070\*\* -0.068\*\*

[0.05] [0.04] [0.03] [0.04] [0.04]

DJ(-1) -0.097\*\*\* -0.115\*\*\* -0.126\*\*\* -0.142\*\*\* -0.136\*\*\*

[0.01] [0.00] [0.00] [0.00] [0.00]

No. of obs. 194

**Dependent variable: ΔASY (December 2016-May 2020)-(1, 0, 0, 0, 0, 1)**

ΔASY(-1) 0.428\*\*\* 0.407\*\*\* 0.393\*\*\* 0.369\*\*\* 0.354\*\*\*

[0.00] [0.00] [0.00] [0.00] [0.00]

ΔSENT -0.302\*\*\* -0.285\*\*\* -0.256\*\*\* -0.244\*\*\* -0.228\*\*\*

[0.00] [0.00] [0.00] [0.00] [0.00]

ΔTRDEF 0.089\*\*\* 0.095\*\*\* 0.110\*\*\* 0.106\*\*\* 0.125\*\*\*

[0.01] [0.01] [0.00] [0.00] [0.00]

ΔTRSH -0.037 -0.045\* -0.049\* -0.046\* -0.052\*

[0.13] [0.10] [0.09] [0.10] [0.08]

ΔINF 0.049\* 0.057\* 0.056\* 0.068\*\* 0.082\*\*

[0.09] [0.07] [0.07] [0.05] [0.03]

ΔEX -0.066\*\* -0.068\*\* -0.078\*\* -0.089\*\* -0.096\*\*

[0.05] [0.05] [0.04] [0.03] [0.02]

ΔDJ -0.096\*\*\* -0.105\*\*\* -0.123\*\*\* -0.130\*\*\* -0.146\*\*\*

[0.01] [0.01] [0.00] [0.00] [0.00]

ΔDJ(-1) -0.064\* -0.070\*\* -0.084\*\* -0.089\*\* -0.085\*\*

[0.06] [0.05] [0.04] [0.03] [0.04]

g(-1) 0.041\* 0.047\* 0.056\* 0.066\* 0.079\*\*

[0.10] [0.08] [0.07] [0.06] [0.04]

SENT(-1) -0.224\*\*\* -0.203\*\*\* -0.192\*\*\* -0.165\*\*\* -0.148\*\*\*

[0.00] [0.00] [0.00] [0.00] [0.00]

TRDEF(-1) 0.045\* 0.049\* 0.060\* 0.067\* 0.079\*\*

[0.10] [0.09] [0.07] [0.06] [0.05]

TRSH(-1) -0.031 -0.036 -0.039 -0.034 -0.032

[0.19] [0.17] [0.15] [0.17] [0.19]

INF(-1) 0.032 0.044\* 0.046\* 0.042\* 0.059\*

[0.16] [0.10] [0.09] [0.10] [0.07]

EX(-1) -0.074\*\* -0.080\*\* -0.085\*\*\* -0.077\*\* -0.083\*\*\*

[0.03] [0.02] [0.01] [0.02] [0.01]

DJ(-1) -0.109\*\*\* -0.123\*\*\* -0.140\*\*\* -0.149\*\*\* -0.162\*\*\*

[0.00] [0.00] [0.00] [0.00] [0.00]

No. of obs. 42

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

*Note*. Figures in brackets denote p-values. Δ denotes first differences, g is the error correction term. \*: p≤0.10; \*\*: p≤0.05; \*\*\*: p≤0.01.

**5 CONCLUSION**

This study extracted quantile-based US EPU risk measures under three alternative definitions, i.e. uncertainty based on news, financial uncertainty, and the dispersion of forecasters’ disagreement. The framework accounted for absolute past EPU in quantile modelling and could handle mixed-frequency data sampling. The analysis applied the QADL-MIDAS model for EPU and compared it to a standard QAR model, spanning the period January 1985 to May 2020. The findings documented that the QADL-MIDAS model outperformed the QAR in terms of out-of-sample performance of predicting conditional quantiles.

Moreover, the analysis used these model-based quantiles to construct three economic policy uncertainty-risk measures related to the probability of extreme EPU realizations (EPUaR), the uncertainty or volatility risk (EPUQR), and the asymmetry of the distribution of future EPU’s realizations (ASY). The results documented that these three risk measures contained sufficient information about i) the evolution of EPU, ii) help in forecasting future realizations of EPU, and iii) can be used to identify the role of certain economic drivers for the dynamics of these EPU risk measures, not only over the period under consideration, but also in specific sub-samples associated with important global events, such as the collapse of the Lehman-Brothers and the Trump’s regime. Moreover, the findings are expected to carry substantial implications about how and to what extend the drivers that determine economic policy uncertainty can impact it at various quantiles, thus, explicitly documenting the potential asymmetric effect on the uncertainty metric. This framework is an ideal case study for illustrating how certain economic and financial headwinds can influence the economic policy uncertainty outlook across the globe. The findings offer a new empirical perspective to existing macroeconomic and financial models, as well as to policymakers, showing that changes in a number of macroeconomic, financial and political conditions can be the key to understand the tail-risk dynamics of economic policy uncertainty. The results also allow to explicitly explore whether at high values (high quantiles) of economic policy uncertainty it does not ‘return to normal’ as the Great Recession recedes; it can be expected to remain relatively high for the foreseeable future absent efforts to address underlying factors, such as political or cultural or societal fragmentation that could be potentially responsible for its elevation. In these ways, the empirical findings provide potential connections (to be explored in the future) between the literature on economic policy uncertainty and the literature documenting the rise of political polarization in the U.S. In that respect, this metric could potentially contain information that not only is endogenous to political undercurrents, but also is reflective of other aspects of policy uncertainty that may contain marginal information about the economy (either on an aggregate basis, or on certain sectors in the economy), especially at such values that the uncertainty permanently affects its future course.

The analysis in the last section can be extended by including more potential drivers of the EPU risk measure, i.e. political and institutional variables, while the entire analysis can be extended to EPU risk measures associated with other countries.

**DATA AVAILABILITY STATEMENT**

The data that support the findings of this study are available from the corresponding author upon reasonable request.

**APPENDIX**

The Quantile Autoregressive Distributed Lag Mixed-Frequency Data Sampling (QADL-MIDAS) regression model is used in forecasting various variables quantiles. In other words, this approach is used to extract model-implied risk measures for a variable, say y. More specifically, to extract variable risk measures, the method is interested in modeling the τ-th quantile of h-step ahead series [y(h)t+h] using the information given at time t. Let Ft+h|t(y(h)) = Pr(y(h)t+h < y|Ft) be the (conditional) cumulative distribution function (CDF) of the variable y, where Ft is the information set at time t. The conditional quantile τ of h-step ahead variable y(h)t+h is given by:

qτ,t+h(y(h)t+h) = F−1t+h|t(y(h)) (A1)

The starting point is the Quantile Auto-Regression (QAR) model introduced by Koenker and Xiao (2006), while the new method extends it to QADL-MIDAS, whereby the regression quantiles depend on past absolute values of the variable y. The AR(p) model for 1-step ahead prediction, which is given by:

p-1 q-1

yt+1 = µ + Σ αj yt−j + εt+1 ≡ µ + ρ yt + Σ βj ∆yt−j + εt+1 (A2)

j=0 j=0

where µ is the intercept and β = (β0, . . ., βp−1) is the vector of autoregressive coefficients. Then, the AR model is written such that ρ, which is

p-1

ρ = Σ αj represents the persistence of inflation and q = p − 1 are the number of lags.

j=0

The modelling approach allows for AR coefficients to be quantile-level dependent, and thus it considers a QAR model given by the following equation:

q-1

qτ (yt+1|Ft) = µτ + ρτ πt + Σ βτ,j ∆yt−j (A3)

j=0

where τ∈(0, 1) is the quantile level and regression coefficients are quantile-specific. When the coefficients in (A3) do not vary with τ, the method goes back to the classic AR model. Conversely, if they are not constant across quantiles, the impact of information contained in Ft on the distribution of yt+1 becomes quantile-specific. The method is interested in forecasting h-step ahead y series quantiles, and thus it reformulates the QAR model as:

q-1

qτ(y(h)t+h|Ft) = µτ + ρτ yt + Σ βτ,j ∆yt−j (A4)

j=0

(A4) implies that the conditional forecasts are formed using a direct forecasting approach. That is, the method regresses the information available at time t on t-h to forecast the t+h quantile. In the proposed model, the h-step ahead conditional quantile of the variable y depends on the current level and on an additional term. The summation term in (A4) can be proxied by a Zt(θ) factor as:

q-1

Zt(θτ) = Σ ωm (θτ) |∆ŷt−m| (A5)

m=0

However, the quantiles and the information set not necessarily pertain to the same frequency and, therefore, would involve past h period of the y variable. The method opts for a specification that avoids parameter proliferation as is typical in MIDAS regressions, and, therefore, takes a specific form for the polynomial ωm using a normalized beta probability density function. Formally, the weights are defined as:

q-1

ωm = [(1 − xm)θ] / [Σ ωm (1 − xm)θ] (A6)

m=0

where xm = (m − 1)/(h − 1). Since ωm depends on a single parameter θ, the model is parsimonious, yet flexible enough to capture complicated dynamics of the variable y. The modelling approach has several advantages. First, using a tightly parameterized polynomial, it avoids potential over-fitting problems even if it adds a large number of lags. Second, the parsimonious beta lag polynomial function ωm allows to specify the model at any sampling frequency (e.g., quarterly), while keeping the information set fixed at a different frequency.

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