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Abstract

We employ a mixed-frequency quantile regression approach to model the time-varying conditional distribution of the US real GDP growth rate. We show that monthly information on the US financial cycle improves the predictive power of an otherwise quarterly-only model. We combine selected quantiles of the estimated conditional distribution to produce measures of uncertainty and skewness. Embedding these measures in a VAR framework, we show that unexpected changes in uncertainty are associated with an increase in (left) skewness and a downturn in real activity. Empirical findings related to VAR impulse responses and forecast error variance decomposition are shown to depend on the inclusion/omission of monthly-level information on financial conditions when estimating real GDP growth's conditional density. Effects are significantly downplayed if we consider a quarterly-only quantile regression model. A counterfactual simulation conducted by shutting down the endogenous response of skewness to uncertainty shocks shows that skewness substantially amplifies the recessionary effects of uncertainty.

JEL-Codes: E210, E240.

Keywords: uncertainty, skewness, quantile regressions, vector autoregressions, MIDAS.

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1 Introduction

The 2007-09 recession has raised researchers and policymakers' attention on the determinants of the conditional distribution of real GDP growth. Following the "growth-at-risk" analysis by Adrian, Boyarchenko, and Giannone (2019), many studies have focused on the information carried by financial indicators when it comes to forecasting changes in the left tail of the distribution of real GDP growth.[1] Correctly quantifying skewness, a prime indicator of economic risk, is crucial for policymakers concerned with risk-management (such as the Federal Reserve, see e.g., Evans, Fisher, Gourio, and Krane (2015)) and, more in general, with the correct design of macroeconomic policies that aim at limiting business cycle costs due to rare but large shocks.

This paper shows that monthly data on financial conditions readily available to policymakers improve the forecast accuracy of the conditional distribution of real GDP growth in an otherwise quarterly data-only model. We augment Adrian et al.'s (2019) quantile regressions framework with monthly realizations of the national financial conditions index (NFCI) (used at a quarterly level by Adrian et al., 2019) by implementing the unrestricted mixed-frequency approach (MIDAS) proposed by Foroni, Marcellino, and Schumacher (2015).[2] We document the superior out-of-sample predictive ability of our MIDAS model with respect to the quarterly data-only framework using the quantile combination approach proposed by Lima and Meng (2017) and via quantile score tests. Then, we construct measures of uncertainty and skewness by combining selected quantiles of the estimated conditional distribution of real GDP growth. Uncertainty is measured as the dispersion of such distribution, while we use a Kelley index for skewness. Both measures display substantial time-dependence and feature abrupt variations in correspondence with extreme events such as the recessions of the early 1980s and the 2007-09 one. Our novel measures are shown to correlate with measures

[1]As pointed out by Stock and Watson (1999) (p. 15), *"[...] the cyclical component of real GDP is a useful proxy for the overall business cycle"*.

[2] For the seminal paper on quantile regressions, see Koenker and Bassett (1978). An analysis of the subsequent methodological advances made in the quantile regression areas is offered by Koenker (2005). An extensive presentation and investigation of the MIDAS approach can be found in Ghysels, Santa-Clara, and Valkanov (2004) and Ghysels, Sinko, and Valkanov (2007).

of real uncertainty and skewness such as the macroeconomic uncertainty proxy estimated by Jurado, Ludvigson, and Ng (2015) and Ludvigson, Ma, and Ng (2021) and the skewness measure based on US companies' sales growth rate employed by Salgado, Guvenen, and Bloom (2019).

In the second part of the paper, we conduct a VAR analysis that models a battery of standard indicators of the business cycle and our measures of uncertainty and skewness. Following an unexpected increase in uncertainty, our VAR points to a significant downturn in real activity along with an increase in left skewness (i.e., lower quantiles responding more than upper ones). Such interaction between changes in uncertainty and skewness could explain the disconnection between quantiles that Adrian, Boyarchenko, and Giannone (2019) find in the data. We find that exogenous changes in uncertainty are responsible for 18% (12%) of the forecast error variance of the unemployment rate (industrial production) at business cycle frequencies. Repeating the same exercise with the uncertainty and skewness measures estimated with quarterly data only, we find the impact of changes in uncertainty on the business cycle to be much lower, with just 6 (2) percent of the forecast error variance of the unemployment rate (industrial production) explained by uncertainty shocks.

In the last part of the paper, we run a counterfactual exercise in which we shut down the endogenous response of skewness to an exogenous variation of uncertainty. We find that muting the response of skewness implies a milder drop in real activity. Hence, skewness acts as a magnifier of the real effects of uncertainty shocks. This "uncertainty-skewness multiplier" is found to be as large as 1.3 in the case of industrial production, i.e., the indirect effect of an uncertainty shock operating via the endogenous response of skewness makes the drop in industrial production 30% larger (than in a counterfactual world in which skewness is not driven by uncertainty shocks). We find a slightly smaller multiplier for unemployment (1.25), and a larger one for hours worked (1.35). Differently, the endogenous response of skewness does not seem to affect prices (the uncertainty-skewness multiplier in this case is 1.05).

Our results point to the importance of: i) considering monthly-frequency information related to the state of financial markets to predict the left tail of the conditional density of the quarterly growth rate of real GDP and compute measures of uncertainty and skewness; ii) modeling skewness in VAR analysis to take into account not only the direct effects that uncertainty can have on real activity, but also the indirect effects via the endogenous response of the left tail of the real GDP density.

The remainder of the paper is structured as follows. Section 2 draws connections with the existing literature. Section 3 documents the performance of our mixed-frequency approach in predicting the conditional density of real GDP growth. Section 4 proposes novel measures of uncertainty and skewness based on selected quantiles of the estimated time-varying conditional density. Section 5 presents VAR investigations involving the above mentioned novel measures and a battery of macroeconomic indicators. Section 6 concludes.

2 Connections with the literature

The closest paper to ours is probably Forni, Gambetti, and Sala (2021a). They combine quantile regressions and structural VARs to model the conditional density of real GDP growth and identify its determinants. They find that the recessionary effects often attributed to second moment shocks are actually driven by shocks to the lower tail of such a conditional density, i.e., "downside uncertainty". Differently, shocks to the higher tail ("upside uncertainty") are mildly expansionary.[3] With respect to Forni, Gambetti, and Sala (2021a), who focus on quarterly data, we show that working with a mixed-frequency approach improves the predictive power of a quarterly data-only model, with implications on moments of interest such as impulse responses and forecast error variance decomposition. Moreover, our emphasis is on the endogenous response of skewness to an uncertainty shock, and the role that skewness plays in magnifying the business cycle effects of such a shock.

[3] See Segal, Shaliastovich, and Yaron (2015) and Rossi and Sekhposyan (2015) for similar decompositions of uncertainty based on the "good"/"bad" uncertainty concepts.

Adrian, Boyarchenko, and Giannone (2019) model the evolution of the conditional density of real GDP growth and show that financial conditions - captured by the national financial conditions index (NFCI) produced by the Federal Reserve Bank of Chicago - are crucial to predict "growth-at-risk", i.e., the evolution of the lower tail of the predicted density.[4] They do so by employing quantile regressions at quarterly frequencies. Our paper shows that mixing frequencies and employing monthly realizations of the NFCI improves the forecasting performance of the quantile regression model, above all as far as skewness ("growth-at-risk") is concerned. As in Adrian, Boyarchenko, and Giannone (2019), we adopt a parsimonious approach for modeling growth-at-risk. Iseringhausen, Petrella, and Theodoridis (2022) propose a data-rich approach to measure expected macroeconomic skewness in the U.S. economy. In line with our results, they find expected macroeconomic skewness to be procyclical. Interestingly, they document a strong correlation between revisions in their novel measure of expected skewness and the main business cycle shock put forth by Angeletos, Collard, and Dellas (2020).

Our paper is related to a number of recent empirical contributions. De Nicolò and Lucchetta (2017) find the quantile regressions approach to be relatively more powerful to assess tail risks than a variety of univariate and multivariate frameworks. González-Rivera, Maldonado, and Ruiz (2019) employ a quantile regression approach to construct a measure of "growth-in-stress", which measures the expected fall in a country's GDP as the global factors that drive world growth are subject to stressful conditions. Ghysels (2014) and Aastveit, Foroni, and Ravazzolo (2017) find that high-frequency information can significantly improve the estimation of density forecasts of macroeconomic variables. Our empirical results point in particular to the relevance of employing monthly data on financial conditions to estimate the conditional density of the growth rate of real GDP. In this sense, our paper connects to Alessandri and Mumtaz (2017), Delle Monache, De Polis, and Petrella (2021), Giglio, Kelly, and Pruitt (2016), and

[4]The NFCI captures the evolution of broad financial conditions based on information on money markets, debt and equity markets, and the traditional and shadow banking systems.

Adams, Adrian, Boyarchenko, and Giannone (2021), which show that financial conditions are important to predict real GDP during the great recession (the former two papers) and macroeconomic risk in general (the latter contributions). Amburgey and McCracken (2022) evaluate the real-time predictive content of NFCI vintages, reinforcing the above mentioned findings. Related papers are Forni, Gambetti, Maffei-Faccioli, and Sala (2021) and Loria, Matthes, and Zhang (2022), who show that identified financial and monetary policy shocks are relevant drivers of macroeconomic risk. Ferrara, Mogliani, and Sahuc (2021) document with Euro area data that a MIDAS approach can help predicting lower frequency macroeconomic risk with higher frequency financial data. Mitchell, Poon, and Mazzi (2021) and Figueres and Jarociński (2020) also work with Euro area data and model the conditional density of real GDP growth. The former work with a MIDAS framework involving a large number of predictors, while the latter work with different indicators of financial conditions. With respect to these papers, we show that the implications of running VAR analysis using measures of uncertainty and skewness constructed with the estimated quantiles of the conditional density of GDP growth (an approach that has recently become popular in the profession) may importantly depend on the high-frequency information on financial conditions, above all when uncertainty shocks are considered.[5] Rossi and Sekhposyan (2015) construct a measure of uncertainty by tracking the time-varying position of the forecast error of the real GDP with respect to its unconditional empirical density. Differently, we employ selected quantiles of the time-varying conditional density estimated with our MIDAS approach to produce novel measures of uncertainty and skewness. Moreover, our paper complements contributions that have stressed the interaction between financial conditions and tail events (Caldara, Scotti, and Zong (2021)), possibly generated by first-moment shocks. Our contribution focuses on the role that higher frequency information can play with respect to a quarterly-only model.

[5] In this sense, a related contribution is Paccagnini and Parla (2021). They show that VAR investigations on the impact of financial uncertainty shocks conducted with low frequency data may be affected by a temporal aggregation bias, an issue that can be tackled by augmenting the information set with higher frequency financial information.

Other departures with respect to the framework proposed by Adrian, Boyarchenko, and Giannone (2019) have been investigated by the literature, i.e., nonlinearities and/or a panel data approach. Clark, Huber, Koop, Marcellino, and Pfarrhofer (2021) cover both such dimensions, while Plagborg-Møller, Reichlin, Ricco, and Hasenzagl (2020) and Reichlin, Ricco, and Hasenzagl (2020) investigate the potentially nonlinear role played by financial indicators in predicting real GDP growth. Our paper also connects with the contributions that have explored the state-dependent effects of uncertainty shocks, typically finding them to be larger during recessions (Caggiano, Castelnuovo, and Groshenny (2014), Caggiano, Castelnuovo, and Nodari (2022)), possibly due to financial frictions (Alessandri and Mumtaz (2019), Alessandri and Bottero (2020)).

From a theoretical modeling standpoint, our evidence points to the need of building up frameworks featuring mechanisms that generate the type of uncertainty-skewness interaction we find in the data. Examples of such mechanisms include downward wage rigidities (Cacciatore and Ravenna (2021)), the zero lower bound (Caggiano, Castelnuovo, and Pellegrino (2017), Basu and Bundick (2017)), a combination of first and second-moment shocks (Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018)), households' high risk aversion (Caggiano, Castelnuovo, and Pellegrino (2021), Pellegrino, Castelnuovo, and Caggiano (2022), Bretscher, Hsu, and Tamoni (2022)), high firm's leverage (Jensen, Petrella, Ravn, and Santoro (2020)), firms' nominal upward pricing bias (Andreasen, Caggiano, Castelnuovo, and Pellegrino (2021)), and the rapid adoption of new technologies (Jovanovic and Ma (2022)). More in general, our findings offer support to theoretical contributions that have investigated the role of uncertainty shocks as drivers of the business cycle (Bloom (2009), Gourio (2012), Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe (2011), Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015), Basu and Bundick (2017), and Born and Pfeifer (2021)). This literature complements studies that have directly focused on the role of skewness shocks (Salgado, Guvenen, and Bloom (2019)).

3 Real GDP growth's conditional density: A MIDAS approach

Let y_{t+h} be the annualized average growth rate of GDP between t and $t+h$ (i.e., $y_{t+h} = \frac{400}{h}\sum_{i=1}^{h} \Delta log(GDP_{t+i})$, Δ is the first-difference operator, and x_t the vector that contains all the conditioning variables. As shown by Koenker and Bassett (1978), the $100(\tau)$-th conditional quantile of y_{t+k} can be estimated by solving the following minimization problem:

$$\hat{\beta}_\tau = \underset{\beta_\tau}{argmin} \sum_{t=1}^{T-h} (\tau 1_{(y_{t+h} \geq x_t\beta)} |y_{t+h} - x_t\beta_\tau| + (1-\tau) 1_{(y_{t+h} \leq x_t\beta)} |y_{t+h} - x_t\beta_\tau|) \qquad (1)$$

where $\tau \in (0,1)$ and $1_{()}$ denotes an indicator variable which takes value "1" if the argument is true and "0" otherwise. The time-varying fitted values of (1), i.e. $\hat{Q}_\tau(y_{t+h}|x_t) = x_t\hat{\beta}_\tau$, are consistent estimators of the $100(\tau)$-th quantile of the objective distribution, given x_t.

We consider the sample 1971Q1-2019Q3 to avoid dealing with the non-market based COVID-19 recession. The quarterly data-only approach by Adrian, Boyarchenko, and Giannone (2019) can be replicated by setting $x_t = \{y_t, NFCI_t\}$. As anticipated above, the alternative we propose is to use an (unrestricted) MIDAS model that features both a lagged realization of the quarterly growth rate and three monthly realizations of NFCI as covariates. Formally, the MIDAS specification features the following set of predictors: $x_t^* = \{y_t, NFCI_{t,m3}, NFCI_{t,m2}, NFCI_{t,m1}\}$.[6] Model (1) can be estimated directly without restrictions on the parameters by replacing x_t with x_t^*.[7]

We evaluate the predictive power of the quarterly data-only vs. the MIDAS models along four different dimensions: i) the regressors' predictive power for different conditional quantiles; ii) the out-of-sample models' point-forecast accuracy in terms of root-mean square error (RMSE) and mean squared error (MAE); iii) the out-of-sample

[6] $NFCI_{t,m_i}$, with $i \in \{1,2,3\}$ is the observation of NFCI at the i-th month of quarter t.

[7] The NFCI is available weekly. Marcellino, Clark, and Carriero (2021) explore the gains of employing weekly indicators when conducting nowcasting exercises, and find them to be mild and not necessarily significant compared to using monthly realizations. The choice of using monthly-level regressors (as opposed to weekly observations) enables us to work with a parsimonious - yet powerful - predictive model.

ability of the model to capture downside risk (using the quantile score on lower quantiles and the quantile-weighted continuous ranked probability score); iv) the evolution of the conditional quantiles delivered by the two models and their ability to timely pick up the arrival of recessionary periods.[8] Given that our proposal is that of exploiting monthly-frequency information to predict the conditional density of the real GDP growth rate at a quarterly frequency, throughout the paper we focus on the one-quarter ahead forecast horizon, i.e., we consider $h = 1$.

3.1 Regressors' predictive power

Table 1 reports the regressors' predictive power for the 10-*th* quantile (left tail), the median (central tendency), and the 90-*th* quantile (right tail) of the time-varying conditional distribution for real GDP growth. We report these selected quantiles because we will employ them to construct our measures of uncertainty and skewness. If the regressors have limited predictive power on the estimated quantiles, then the conditional density is not precisely estimated (similar tests to validate the quantile regression model are carried out by Adrian, Boyarchenko, and Giannone (2019) and Forni, Gambetti, and Sala (2021a)). Table 1 documents the statistical significance of past realizations of the NFCI not only at a quarterly frequency, but also for the monthly realizations of our MIDAS model, above all for the tails of the conditional density. Notably, realizations of the NFCI at different months are associated with alternating signs, a "dynamic correction" that would not be possible to detect with more parsimonious but restricted MIDAS models.[9] Differently, the significance of monthly NFCI realiza-

[8]The choice of the regressors in our MIDAS framework represents a natural extension of the quarterly-only model proposed by Adrian, Boyarchenko, and Giannone (2019). The limited number of regressors of our framework is also intended to tackle the parameter proliferation problem often arising when dealing with quantile regressions with mixed-frequency data. For a formal algorithm to tackle this issue, see Lima, Meng, and Godeiro (2020).

[9]This correction is driven by the evolution of the NFCI, whose first difference may take different signs at a monthly frequency within the quarter before a recession. For instance, NFCI at a monthly level registered a lower value in August 2008 with respect to July 2008, to then substantially increase when moving from August to September 2008.

tions is not present for the median.[10] Past values of real GDP growth are significant for all the considered quantiles in both models.

The evidence so far suggests that monthly observations of the NFCI carry predictive power for the target conditional density. However, while being a necessary condition for our MIDAS model to be preferred to the quarterly-only framework, we have not shown yet that our MIDAS approach is statistically superior from a forecasting standpoint. To do so, we now turn to an out-of-sample comparison.

3.2 Out-of-sample predictive power

We evaluate the out-of-sample predictive power of the competing models at hand in terms of both point-forecast performance and ability to capture tail risk. Following Adrian, Boyarchenko, and Giannone (2019), we work with a recursive forecasting scheme, using as initial estimation sample 1971Q1-1989Q4 (the out-of-sample forecast evaluation sample ends in 2019Q3). First, we assess the point-forecast ability of the competing models. As stressed by Carriero, Clark, and Marcellino (2020), even if quantile regression models are not explicitly designed to obtain point estimates, it can be useful to know how such models perform as far as the central tendency of the distribution is concerned. Following Lima and Meng (2017), we approximate the mean of the one-step ahead real GDP growth's conditional density by adequately combining its conditional quantiles (an approach termed "quantile combination approach"). Formally, the one-quarter ahead point-forecast implied by our quantile regressions is computed as:

$$\hat{y}_{t+1} = \sum_{\tau \in J} \frac{1}{n} \hat{Q}_{\tau}(y_{t+1}|x_t) \tag{2}$$

where n is the length of J, and $J = \{0.05, 0.1, 0.25, 0.5, 0.75, 0.9, 0.95\}$. We then use the so-obtained point forecasts to compare the relative out-of-sample forecasting performance of the quarterly-only vs. MIDAS frameworks in a standard fashion.[11]

[10] The correlation between the median with the MIDAS model and that estimated with the the quarterly data-only model is 0.97. Moreover, the two series are visually indistinguishable.

[11] Considering the mean of the distribution as point-estimate (as opposed to, for instance, the median) is pivotal, since the quantile regressions model provides a probability assessment which need

Table 2 documents the outcome of this exercise. It reports the relative root mean square error (RMSE) and mean absolute error (MAE) of the MIDAS model (the RMSE and MAE of the quarterly-only model are normalized to one).[12] Moreover, it reports the p-value of a Diebold-Mariano test conducted on the basis of the point forecasts computed as explained above. Both the RMSE and the MAE point to the MIDAS model as the better performing one. Reassuringly, this indication is also supported by the Diebold-Mariano test, which points to the statistical superiority (at conventional levels) of the MIDAS model vs. the quarterly-only competitor.

Another test we conduct is the quantile score, which is based on the assessment of the models' ability to capture tail risk (Carriero, Clark, and Marcellino (2020)). We evaluate the relative out-of-sample accuracy of the 5-*th* and 10-*th* conditional quantiles. While the 5-*th* quantile is a standard benchmark for these tests, the choice of the 10-*th* quantile is motivated by the fact that this is the lower quantile of interest that we will use to construct our novel uncertainty and skewness measures. Conditional on these quantiles, we compute the quantile score as follows:

$$QS^{\tau}_{t+1} = (y_{t+1} - \hat{Q}_{\tau}(y_{t+1}))(\tau - 1_{(y_{t+1} \leq \hat{Q}_{\tau}(y_{t+1}))})$$

where $1_{(y_{t+1} \leq \hat{Q}_{\tau}(y_{t+1}))}$ has a value of 1 if the GDP growth realization is at or below the τ-*th* quantile and 0 otherwise.

The advantage of using the quantile score is that it is associated with an asymmetric loss function. Hence, the assessment of the accuracy of the estimated quantiles assigns a larger weight to overpredictions than to underpredictions. This implies that missing deep recessions is more costly (according to this loss function) than missing strong expansions, an assessment in line with the risk management approach undertaken by policymakers (Evans, Fisher, Gourio, and Krane (2015)). In addition, the out-of-sample quality of the predictive density can be tested via the quantile-weighted continuous ranked probability score (qwRPS) proposed by Gneiting and Ranjan (2011),

not be symmetric.

[12] We also considered the mean absolute percentage error and obtained similar results to those documented here.

which is a weighted sum of quantile scores at a range of quantiles with an asymmetric scoring function that gives more weight to the left tail quantiles. The quantile-weighted continuous ranked probability score is defined as:

$$qwCRPS_{t+1} = \frac{2}{n} \sum_{\tau \in J} v(\tau) QS^{\tau}_{t+1}$$

where $v(\tau) = (1-\tau)^2$, n is the length of J, and $J = \{0.05, 0.1, 0.25, 0.5, 0.75, 0.9, 0.95\}$.

Table 3 reports the results of the above-mentioned tests. Overall, the MIDAS model is relatively more accurate in capturing tail risk out-of-sample. We find that $\bar{QS}^{0.05}_{MIDAS}/\bar{QS}^{0.05}_{Quart.} = 0.85$ and $qw\bar{CRPS}_{MIDAS}/qw\bar{CRPS}_{Quart.} = 0.96$ (p-values are respectively 0.08 and 0.12).[13] Similar results are obtained considering the 10-*th* quantile when computing the quantile score and according to the in-sample version of the tests.[14] To conclude, this evidence points to a competitive performance of the MIDAS model when compared to the one of the quarterly-only model, both in terms of point-forecast and in the ability of capturing tail risk. Violations of the lower quantiles are found to be smaller in magnitude than those implied by the quarterly-only framework (QS) and the overall quality of the predictive densities increases ($qwCRPS$).

3.3 Evolution of conditional densities

Figure 1 (upper panels) shows the (in-sample) evolution of selected conditional quantiles delivered by the two models. The general pattern appears to be the same in terms of median value and quantile dispersion, with the lower quantile of the distributions moving much more than the upper quantile. However, a clear difference arises when comparing the relative ability of the two models to pick up recessions, with the conditional density implied by the MIDAS model adjusting more timely than the one predicted by the model exploiting the information carried by the NFCI at a quarterly frequency only. The actual realization of the real GDP growth rate is below the 10-*th*

[13] $\bar{QS}_{MIDAS}$ and $\bar{QS}_{Quart.}$ denote the sample average of the quantile scores in the forecasting period considered. The same holds true for $qw\bar{CRPS}_{MIDAS}$ and $qw\bar{CRPS}_{Quart.}$

[14] Out-of-sample coverage measures for quantiles of interest are very similar for the two models. The percentage of realizations falling below the 5-*th* (10-*th*) quantile is 7.6% (19.3%) for the MIDAS model and 10.0% (19.3%) for the quarterly one.

quantile of the quarterly-only model's conditional density for four out of six recessions. Differently, the MIDAS model fails to fully pick up only the downturn in early 1990s and the "dot-com" bubble.[15]

Table 4 collects the figures obtained by evaluating the cumulative distributions estimated with the two competing models at the actual GDP growth rate realization during extreme events.[16] We focus on the US recessions (as identified by NBER). The table points to two findings. First, adding realizations of the NFCI enhances the predictive power of the quantile regressions model when it comes to the "growth-at-risk" events (the recessions). Second, monthly information on financial conditions work in favor of improving the quantile regressions' ability to estimate a non-zero probability of a large negative realization of output growth in the following quarter. The example of 1980Q2 recession is instructive. Evaluating the cumulative distributions functions delivered by the two models at the realization, we obtain 0.03 with the quarterly-only model, and 0.18 with our MIDAS framework. The implication is that the actual realization of GDP growth in 1980Q2 is more consistent with the ex-ante conditional density produced with the MIDAS approach than with the quarterly-only approach, a statement which holds true also for the 2008Q4 recession.

All in all, the empirical evidence provided above points to our MIDAS approach as a competitive one with respect to the quarterly data-only framework.

4 Macroeconomic uncertainty and skewness measures

We derive measures of macroeconomic uncertainty and skewness by respectively quantifying the time-varying dispersion and asymmetry of the conditional density of real GDP growth estimated with our MIDAS framework.[17]

[15]Exercises based on out-of-sample forecasts result in a similar pattern.

[16]Following Adrian, Boyarchenko, and Giannone (2019), we consider smoothed conditional densities produced by fitting the skewed t-distribution of Azzalini and Capitanio (2003) to the estimated quantiles.

[17]For a similar strategy behind the construction of measures of uncertainty and skewness, see Salgado, Guvenen, and Bloom (2019) and Forni, Gambetti, and Sala (2021a). Rossi and Sekhposyan (2015) and Rossi, Sekhposyan, and Soupre (2019) employ the empirical density of the prediction error regarding the real GDP growth computed by working with survey expectations to derive measures

4.1 Uncertainty

Uncertainty at time t is defined as:

$$UNC_t = \hat{Q}_{0.9}(y_{t+1}|x_t) - \hat{Q}_{0.1}(y_{t+1}|x_t) \tag{3}$$

The logic behind this characterization of uncertainty is that, conditional on our predictive analysis, uncertainty can be proxied by the variance of the conditional distribution of output growth. The intuition is the following. In periods of high uncertainty, agents' expectations - which in our case are expressed in the form of a complete probability assessment over the future realization of GDP growth - are disperse. Hence, agents assign a positive probability to the occurrence of a wide set of possible states of the world. Conversely, in periods of low uncertainty, the probability of events on the tail of the conditional density is lower.

Figure 2 (top panels) plots our uncertainty measure constructed as in (3). It is clearly countercyclical, with peaks during recessions. As revealed by the top-left panel, our uncertainty proxy is clearly correlated with the macroeconomic uncertainty series proposed by Jurado, Ludvigson, and Ng (2015) (correlation coefficient: 0.65). The top-right panel reveals that a positive correlation is also present when considering the financial uncertainty measure recently proposed by Ludvigson, Ma and Ng (2021). However, said correlation (0.43) suggests that our measure is likely to capture macroeconomic uncertainty more than financial uncertainty. This is not surprising, given that our measure of uncertainty is based on time-varying quantiles of real GDP growth's conditional density.[18]

of uncertainty. For a discussion on measures of uncertainty based on conditional densities, see Rossi (2021).

[18]The distinction between financial and macroeconomic uncertainty is relevant when it comes to isolating uncertainty shocks. According to Ludvigson, Ma, and Ng (2021), financial uncertainty shocks (as opposed to macroeconomic uncertainty shocks) are likely to be drivers of the US business cycle. Differently, Carriero, Clark, and Marcellino (2019) and Forni, Gambetti, and Sala (2021b) point to macroeconomic uncertainty as a relevant driver of the business cycle. For related papers pointing to both types of shocks as possible drivers of the US business cycle, see Angelini and Fanelli (2019) and Angelini, Bacchiocchi, Caggiano, and Fanelli (2019).

4.2 Skewness

The estimated conditional density of real GDP growth can also be exploited to construct a measure of macroeconomic skewness. Following Salgado, Guvenen, and Bloom (2019), the indicator of skewness is based on the normalized Kelley index (Kelley (1974)), which is defined as:

$$SKEW_t = \underbrace{\frac{\hat{Q}_{0.9}(y_{t+1}|x_t) - \hat{Q}_{0.5}(y_{t+1}|x_t)}{\hat{Q}_{0.9}(y_{t+1}|x_t) - \hat{Q}_{0.1}(y_{t+1}|x_t)}}_{\text{Right tail share}} - \underbrace{\frac{\hat{Q}_{0.5}(y_{t+1}|x_t) - \hat{Q}_{0.1}(y_{t+1}|x_t)}{\hat{Q}_{0.9}(y_{t+1}|x_t) - \hat{Q}_{0.1}(y_{t+1}|x_t)}}_{\text{Left tail share}} \in [-1, 1] \quad (4)$$

This measure offers a straightforward decomposition of the share of total dispersion which is attributable to the left and the right tails of the time-varying conditional distribution. Positive values indicate that the right tail is accountable for more than one-half of the total dispersion, so that the distribution is right skewed. Conversely, negative values of the Kelley index signal vulnerable growth (left skewness). The normalization is crucial to make valid comparisons between the skewness of the $t-$specific distributions, since it eliminates the distributing influence of the variance, which could potentially bias the measure.

The measure of skewness obtained using (4) and the MIDAS model is plotted in Figure 2 (lower panels). The main indication that arises is that also macroeconomic skewness fluctuates substantially over time, and distributions become particularly left skewed right before or during recessions.[19] It is of interest to compare our measure of skewness over the CBOE skewness index (which measures the perceived tail risk of the distribution of S&P500 returns over a 30-day horizon) and the one based on US companies' sales growth rate proposed by Salgado, Guvenen, and Bloom (2019). The first one is almost orthogonal to our index. Differently, the second one is positive correlated to ours (correlation: 0.25). This evidence confirms that our novel measure of skewness - very much like the measure of uncertainty presented above - is naturally interpreted as macroeconomic skewness, more than financial skewness.[20]

[19] Our Appendix shows that our measures of uncertainty and skewness, which are based on in-sample forecasts of the conditional density of real GDP growth, are robust to moving to an out-of-sample forecasting exercise based on the 1971Q1-1989Q4 initial sample and a recursive window.

[20] The not particularly high (although positive and significant) correlation with Salgado et al.'s

5 VAR analysis

Equipped with our measures of uncertainty and skewness, we run a VAR analysis to investigate the role that unexpected variations in these two measures may have played in shaping the US business cycle. We do so by modelling the following variables for the period 1971Q1-2019Q3:

$$X_t = \begin{bmatrix} 100log(S\&P500) \\ Uncertainty \\ Skewness \\ 100log(Wages) \\ 100log(CPI) \\ 100log(Per\ Capita\ Hours) \\ Unemployment \\ 100log(Industrial\ Production) \\ Shadow\ rate \end{bmatrix}$$

This set of modeled variables is standard in the literature (see e.g., Bloom (2009), Jurado, Ludvigson, and Ng (2015)).[21] Given the presence of the zero lower bound in our sample, we model the shadow rate proposed by Wu and Xia (2016) instead of the federal funds rate.[22] On top of the usual macroeconomic indicators of the business cycle, we also model the novel measures of uncertainty and skewness obtained with our MIDAS approach. We orthogonalize the residuals of the reduced-form VAR by assuming a recursive structure. No particular economic meaning is attributed to the relative position of uncertainty and skewness in our vector (we follow the ordering of Salgado, Guvenen, and Bloom (2019)). However, it is worth noting that swapping their position leads to similar results. To ease interpretation, we model the measure of

measure might be explained by the fact that the latter is a measure of cross-sectional skewness, while ours is constructed on the basis of an aggregate real activity indicator (real GDP).

[21]Bloom (2009) considers employment, while we model the unemployment rate because the latter is often at the center of debates regarding the labor market and the stance of the business cycle. The correlation between the yearly growth rate of non-farm employment and the unemployment rate in our sample is -0.41. Our results are robust to replacing the unemployment rate with employment.

[22]Our results are robust to the employment of the alternative measure of the shadow rate proposed by Krippner (2020).

skewness in the VAR with its sign flipped around, so that a rise in skewness identifies an increase in dispersion of the *left* tail of the real GDP distribution relative to the *right* tail (i.e., left skewness). We estimate the VAR including 2 lags as suggested by the Hannan-Quinn information criterion.

5.1 Uncertainty, skewness, and the business cycle: Evidence

Figure 3 documents the impulse responses to an one-standard deviation unexpected increase in uncertainty. Such responses are similar to those typically proposed by the literature, i.e., an increase in uncertainty is correlated with a temporary stock market bust, a decline in real activity, an increase in the unemployment rate, and a decrease in prices. These responses are statistically significant and long-lasting, with industrial production, hours, and unemployment going back to their pre-trend level after about three years. A novel result is the strong response of skewness (i.e., a deterioration of the left tail of the density of the real GDP growth), which suggests that uncertainty and skewness can hardly be thought of as independent processes. This finding is consistent with the empirical results documented by Hengge (2019), who shows that measures of uncertainty can significantly predict the lower tail of real GDP growth in a variety of countries.

Table 5 documents the forecast error variance decomposition analysis at various horizons. This analysis suggests that unexpected changes in uncertainty are associated to economically relevant business cycle movements - the four-year ahead contribution to industrial production, the unemployment rate, and hours worked is estimated to be (respectively) 12% for the first variable, and 18% for the latter two. Uncertainty is also a driver of skewness, with a contribution to the latter's forecast error variance of about 11% after four years.[23]

[23] According to our VAR, skewness "shocks" explain about 56% of the 4-year ahead forecast error variance of skewness. While not being the focus or our paper, this result confirms that skewness shocks are also present in the macroeconomic environnment, an evidence in line with Salgado, Guvenen, and Bloom (2019).

5.2 Uncertainty, skewness, and the business cycle: Frequency matters

The impulse responses documented above are conditional on a VAR estimated with uncertainty and skewness measures obtained with our MIDAS framework. But how relevant is it to account for monthly observations of financial conditions when it comes to constructing measures of uncertainty and skewness with the ultimate goal of understanding their conditional correlations with the business cycle? In other words, how would our impulse responses and variance decomposition analysis look like if we instead employed measures of uncertainty and skewness constructed with a quarterly data-only approach? To address these questions, we re-run our VAR analysis by replacing our measures of uncertainty and skewness with those obtained by working with the conditional density of real GDP growth estimated only with quarterly observations.

Figure 4 contrasts our baseline impulse responses with those obtained with measures of uncertainty and skewness obtained with quantiles estimated with quarterly data only. Such a Figure - which focuses on the responses of prices, hours, unemployment, and industrial production to innovations in uncertainty - reveals that impulse responses produced with measures of uncertainty and skewness obtained with quarterly data only approach tend to underestimate the role of uncertainty innovations for the business cycle, with the peak responses of unemployment and industrial production being more than halved with respect to the baseline ones, and those of prices being much milder.

The forecast error variance decomposition analysis documented in Table 6 confirms the biases implied by the use of measures of uncertainty and skewness computed via quantile regressions relying on financial quarterly data-only. Just 6% of the four-year ahead forecast error volatility of the unemployment rate and 2% of industrial production is associated with unexpected changes in uncertainty. This is in contrast with the evidence documented in Table 5, which points to a contribution almost three times larger for the unemployment rate and six times larger for industrial production.

What is the source of the discrepancies between impulse responses documented above? Figure 5 plots the series of the unexpected changes in uncertainty according to the two models we are contrasting, i.e., the MIDAS model and the quarterly data-only framework. As one can easily see, using quarterly data-only has got severe implications when it comes to correctly quantifying the size of such changes in crucial moments of the US economic history. Large recessions, and in particular the great recession, are associated with large positive changes in uncertainty according to the MIDAS model, but much milder changes according to the quarterly data-only framework. This evidence offers a *rationale* for the discrepant impulse responses documented in Figure 4, i.e., the quarterly data-only model underestimates the size of the unexpected positive changes in uncertainty and, therefore, the impact of such changes on real activity.

Wrapping up, our main finding in this Section is that omitting monthly information on financial conditions when predicting the conditional density of real GDP growth has got implications not only for the estimated conditional densities *per se*, but also on the moments implied by such densities.

5.3 The uncertainty-skewness multiplier

As anticipated in our Introduction, recent theoretical contributions have put forth mechanisms that lead to a skewed response of real activity to an uncertainty shock (Cacciatore and Ravenna (2021), Caggiano, Castelnuovo, and Pellegrino (2017), Basu and Bundick (2017), Caggiano, Castelnuovo, and Pellegrino (2021), Pellegrino, Castelnuovo, and Caggiano (2022), Jensen, Petrella, Ravn, and Santoro (2020), Andreasen, Caggiano, Castelnuovo, and Pellegrino (2021), Jovanovic and Ma (2022), and Bretscher, Hsu, and Tamoni (2022)). It is of interest to dig deeper to understand how large a role the endogenous response of skewness plays in transmitting, and possibly magnifying, uncertainty shocks to real activity. We address this question by running a counterfactual with our baseline VAR in which we shut down the response of skewness and compare the factual and counterfactual impulse responses of the same selected variables we have already focused on (price level, hours, unemployment, industrial production).[24] Figure 6 documents the outcome of this exercise. The responses computed under the counterfactual assumption of skewness not responding to uncertainty shocks point to a less severe recession and a more gradual return to the pre-shock paths for unemployment and industrial production. The "uncertainty-skewness" multiplier (assessed by considering the peak responses of these two variables) is large: the response of skewness amplifies the impact of the uncertainty shock on industrial production and hours worked of 30% and 35%, while on unemployment of about 25%. Differently, the impact on inflation is much smaller, i.e., the multiplier is about 5%. The role of skewness is also reflected in the more volatile impulse responses to an uncertainty shock in the baseline scenario. The standard deviation of the impulse response of prices is just 5% larger, but the standard deviation of industrial production and unemployment is about 40% larger, and that of hours worked is about 47% larger.

In Figure 7 we show that our results are robust to i) changes in lag specification, ii) different orderings, and iii) an alternative identification scheme which relaxes the baseline recursive structure. In particular, when we identify uncertainty and skewness "shocks" through the max-share approach proposed by Uhlig (2003), the relevance of skewness as transmission channel is found to be even larger, i.e., the endogenous response of skewness doubles the real effects of uncertainty shocks.[25]

The evidence in Figure 6 and 7 points to the role played by skewness as amplifier of the real effects of uncertainty shocks. This reduced-form evidence offers empirical support to the above mention structural models that feature mechanisms that generate endogenous skewness in response to uncertainty shocks.

[24] Our counterfactual scenario is constructed by subjecting the economy to fictitious shocks to skewness that fully counteract the effects of the uncertainty shock on skewness (Sims and Zha (1995)). For references on the use of fictitious shocks in counterfactual VAR investigations, see Bernanke, Gertler, and Watson (1997), Hamilton and Herrera (2004), and Kilian and Lewis (2011). A discussion on this way of running counterfactual simulations vs. alternative ones can be found in Antolín-Díaz, Petrella, and Rubio-Ramírez (2021) and McKay and Wolf (2022).

[25] Identification is achieved by requiring the uncertainty shock to generate the largest response (increase) in uncertainty for the first year after the shock. The skewness shock (which we need to run our counterfactual simulation) is identified as the innovation that: i) is orthogonal to the uncertainty disturbance; and ii) generates the largest increase in skewness for the first year. For a similar identification strategy to disentangle uncertainty and financial shocks, see Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2016).

6 Conclusions

This paper shows that employing monthly frequencies of financial conditions improve the predictive power of an otherwise quarterly data-only quantile regressions framework when it comes to modeling the conditional density of real GDP growth. We support this statement with a battery of metrics and statistical tests. Then, we use our mixed frequency quantile regression approach to construct novel measures of uncertainty and skewness, which are obtained by combining selected estimated quantiles. Equipped with these novel measures, we run VAR analysis to quantify the relevance of unexpected changes in uncertainty and skewness for the business cycle. We find such changes to be statistically and economically connected to variations in real activity. A different picture emerges when computing measures of uncertainty and skewness based on a time-varying conditional density of real GDP growth estimated without taking information on financial conditions available at a monthly frequency. In particular, the contribution of uncertainty shocks as drivers of the business cycle is underestimated. Finally, a counterfactual exercise computed by shutting down the endogenous response of skewness to an uncertainty shock reveals the existence of an "uncertainty-skewness multiplier", i.e., endogenous skewness acts as an amplifier of the real effects of uncertainty shocks.

Our results suggest that early-warning models on vulnerable real GDP growth should embed financial information available at a monthly frequency because it carries relevant information to correctly assess tail risks, uncertainty, and their empirical links with the business cycle. From a theoretical modeling standpoint, our VAR counterfactual exercise points to the need of modeling frictions able to skew the distribution of real activity in response to changes in uncertainty.

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Tables and Figures

Panel A: Predictive power quarterly model

Predictors	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$
Constant	-0.59 (0.31)	2.28*** (0.00)	4.79*** (0.00)
GDP	0.19* (0.09)	0.16** (0.03)	0.46*** (0.00)
NFCI	-1.86*** (0.00)	-0.71** (0.03)	0.33 (0.50)

Panel B: Predictive power MIDAS model

Predictors	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$
Constant	-0.64* (0.05)	2.14*** (0.00)	4.83*** (0.00)
GDP	0.25*** (0.00)	0.22** (0.03)	0.45*** (0.00)
NFCI_{m3}	-7.89*** (0.00)	-1.35 (0.57)	5.02* (0.06)
NFCI_{m2}	12.23*** (0.01)	0.61 (0.87)	-9.92** (0.03)
NFCI_{m1}	-6.26*** (0.01)	-0.07 (0.97)	5.25** (0.01)

Table 1: **Regressors' predictive power for the 10th, 50th, and 90-th quantile: MIDAS and quarterly model**. P-values in brackets. Standard errors computed via bootstrap techniques (10,000 replications). Similar results are obtained with the rank inversion proposed in Koenker (2005).

	MIDAS model/Quarterly model
RMSE	0.975*** (0.00)
MAE	0.976** (0.01)

Table 2: **Point-forecast accuracy**. Ratios of Root Mean Square Errors and Mean Average Errors computed by considering a recursive forecasting exercise. Initial estimation sample: 1971Q1-1989Q4. Out-of-sample period: 1990Q1-2019Q3. Values lower than one point to the superiority of the MIDAS model in a predictive sense. P-values of the Diebold and Mariano (1995) test in brackets.

	Out of sample	In sample
$\bar{QS}^{0.05}_{MIDAS}/\bar{QS}^{0.05}_{Quart.}$	0.85* (0.08)	0.86* (0.08)
$\bar{QS}^{0.1}_{MIDAS}/\bar{QS}^{0.1}_{Quart.}$	0.96 (0.15)	0.91 (0.11)
$qw\bar{CRPS}_{MIDAS}/qw\bar{CRPS}_{Quart.}$	0.96 (0.12)	0.94 (0.12)

Table 3: **Density accuracy: MIDAS vs. quarterly model**. Ratios of mean quantile scores for 5-th and 10-th quantiles and quantile-weighted continuous ranked probability scores - both in and out-of-sample (estimation sample 1971Q1-1989Q4, and out-of-sample period 1990Q1-2019Q3). Values lower than one point to the superiority of the MIDAS model in a predictive sense. P-values of the Diebold and Mariano (1995) test in brackets.

	Quarterly model	MIDAS model
1975Q1	0.17	0.24
1980Q2	0.03	0.18
1982Q1	0.11	0.10
1990Q4	0.00	0.03
2001Q3	0.02	0.02
2008Q4	0.00	0.10

Table 4: **Probability of deep recessions: MIDAS vs. quarterly model**. Models' cumulative density functions evaluated at the realization of GDP growth rate in different points in time (i.e., the starkest drop for each NBER US recession). Smoothed conditional densities produced by fitting the skewed t-distribution of Azzalini and Capitanio (2003) to estimated quantiles (as in Adrian et al. (2019)). Quantiles considered: 10th, 25th, 75th and 90th.

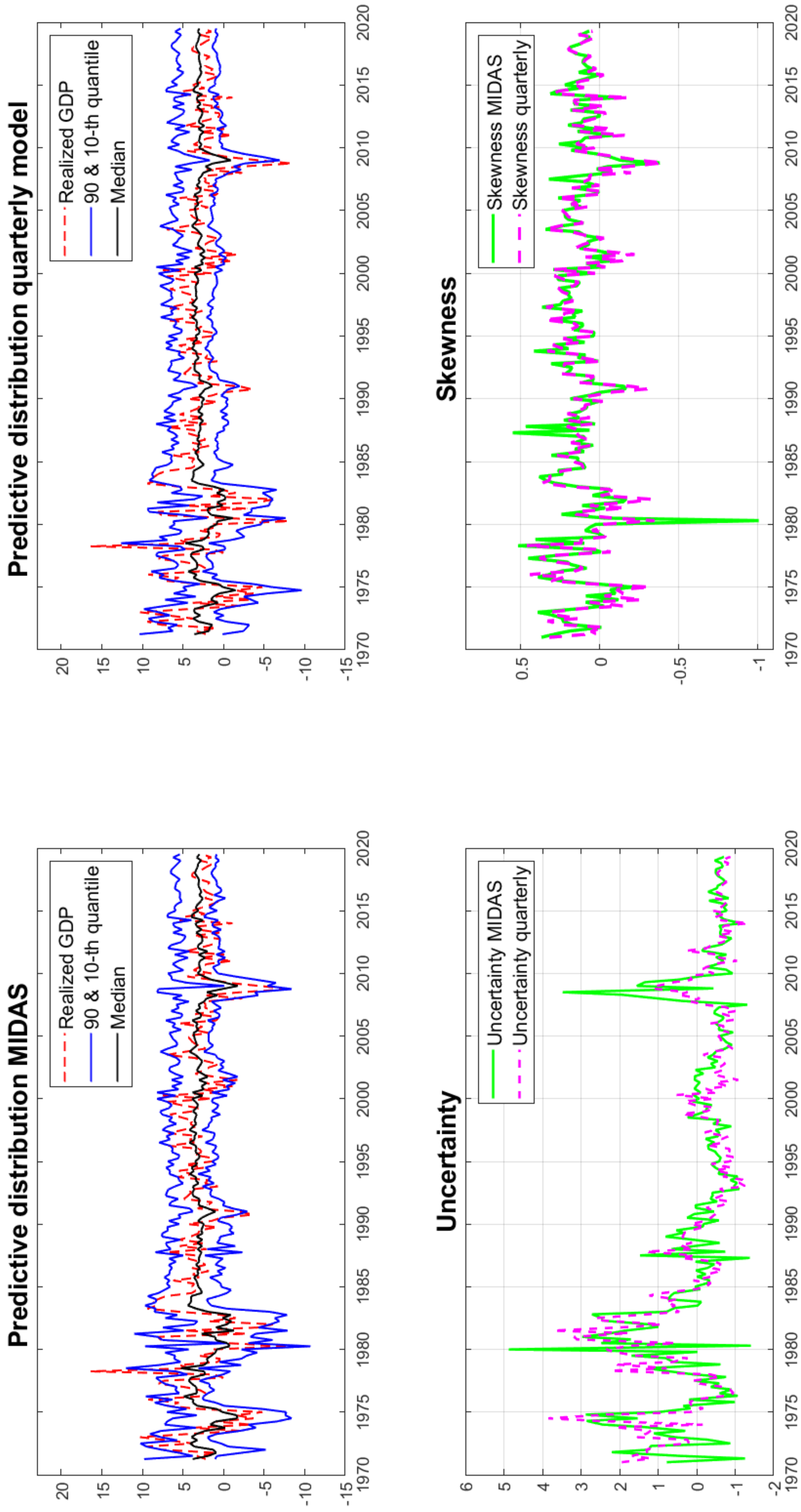

Figure 1: **MIDAS model vs. quarterly model: Predictive densities of the growth rate of real GDP and implied uncertainty and skewness indices**. Forecasting horizon: One quarter.

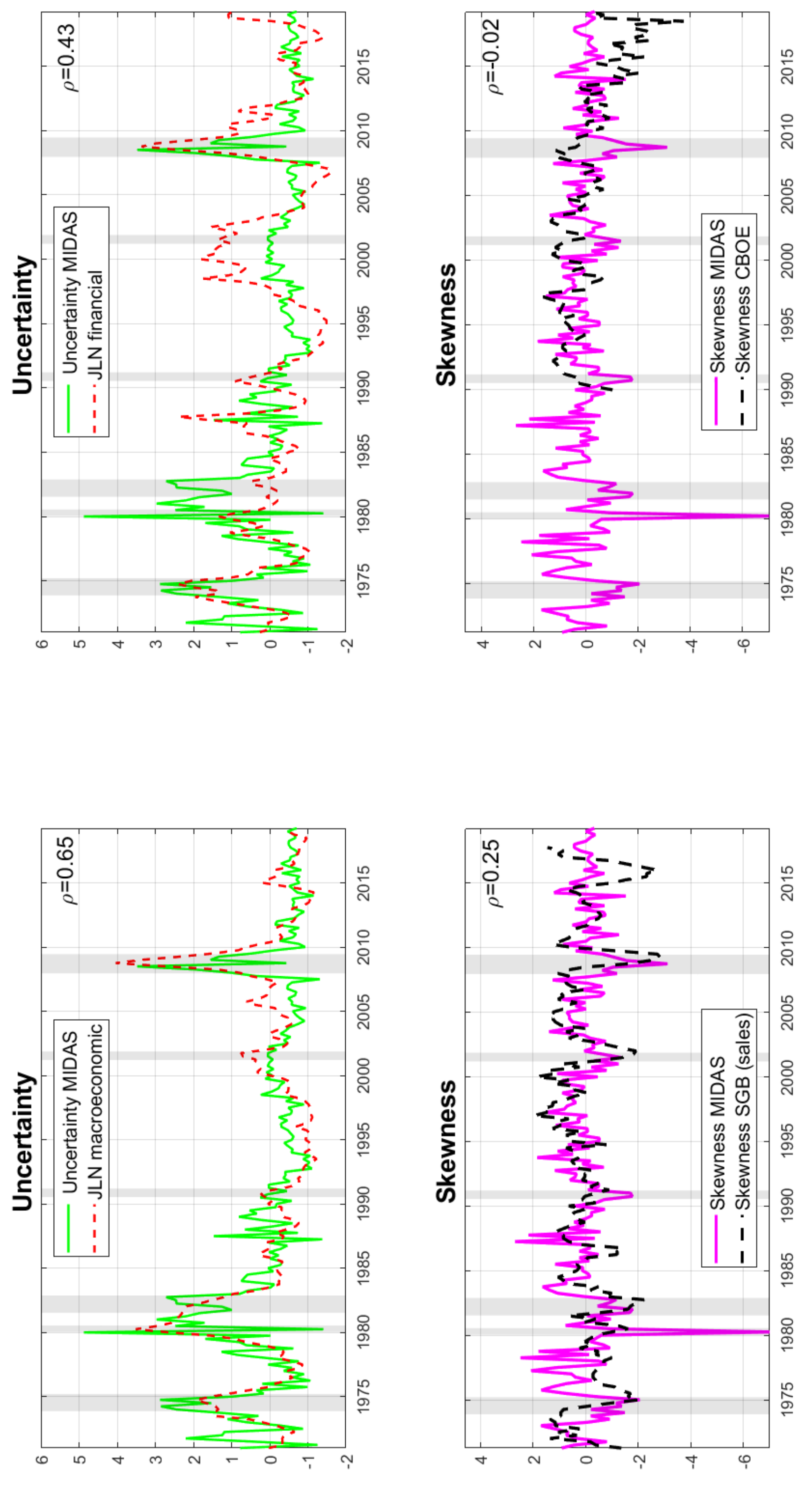

Figure 2: **Uncertainty and skewness measures estimated with the MIDAS model: Comparison with existing indices**. Uncertainty: Macro and financial uncertainty ($h = 1$ quarter) proposed by Ludvigson, Ma, and Ng (2019). Skewness: CBOE skewness index and skewness measure of Salgado, Guvenen, and Bloom (2019) (based on companies' sales growth rate). Indices are standardized for comparison. Shaded vertical bars indicate NBER recessions.

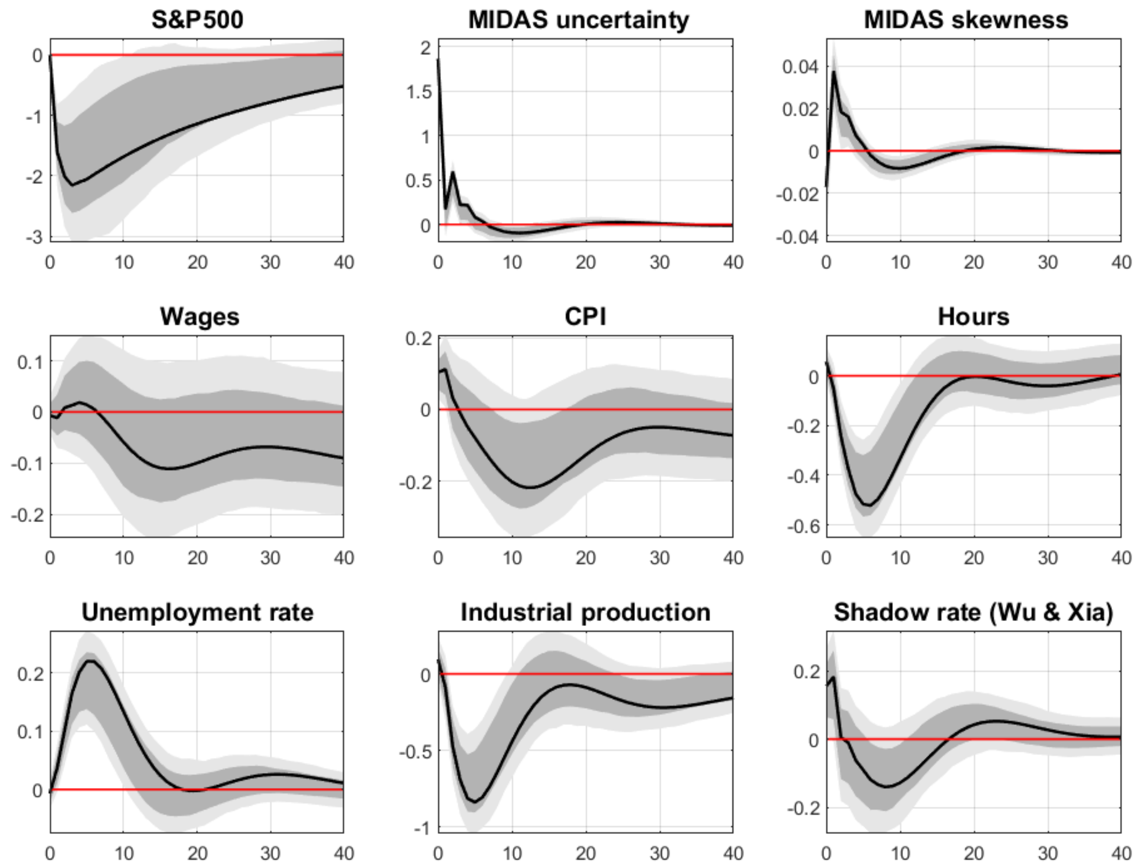

Figure 3: **Impulse responses to an unexpected change in uncertainty - uncertainty and skewness measures computed with the MIDAS model**. Size of the change: One standard deviation. VAR model featuring 2 lags as suggested by the Hannan-Quinn information criterion. Bootsrapped confidence bands: 68% and 90%.

Variable	h=0	h=4	h=16	h=40
S&P500	0	6.40	8.53	9.60
Uncertainty	99.21	80.36	68.53	65.91
Skewness	2.09	11.05	11.42	11.24
Wages	0.05	0.06	1.01	1.43
CPI	6.03	1.24	4.76	3.56
Hours	1.33	14.26	18.25	12.05
Unemployment rate	0.15	16.24	17.62	14.08
Industrial Production	1.09	14.08	12.29	10.45
Shadow rate	3.79	1.84	3.06	2.74

Table 5: **Unexpected change in uncertainty: Forecast error variance decomposition - baseline VAR framework**. Measures of uncertainty and skewness estimated with the MIDAS model.

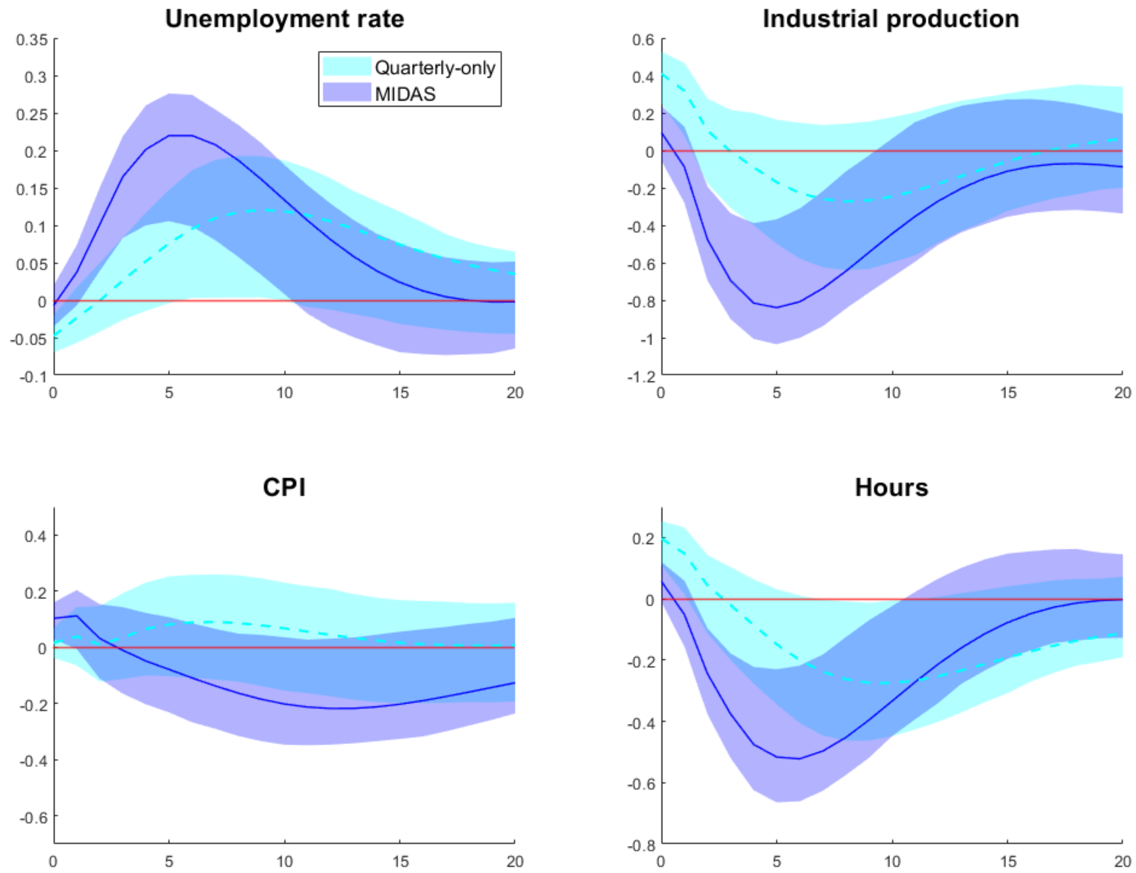

Figure 4: **Impulse responses of selected variables to an unexpected change in uncertainty - VARs embedding measures of uncertainty and skewness estimated with the MIDAS model vs. with the quarterly model**. Dark blue: MIDAS. Light blue: Quarterly data-only. Bootstrapped confidence bands: 90%

Variable	h=0	h=4	h=16	h=40
S&P500	0	0.04	0.15	0.24
Uncertainty	94.08	61.11	55.48	53.80
Skewness	39.82	23.05	21.07	20.58
Wages	2.62	1.68	1.55	1.06
CPI	0.14	0.32	0.62	0.48
Hours	15.98	2.29	6.88	6.47
Unemployment rate	7.12	1.24	6.53	6.02
Industrial Production	19.61	2.75	2.05	1.65
Shadow rate	20.02	13.87	9.95	8.54

Table 6: **Unexpected change in uncertainty: Forecast error variance decomposition - alternative VAR framework**. Measures of uncertainty and skewness estimated with the quarterly-only model.

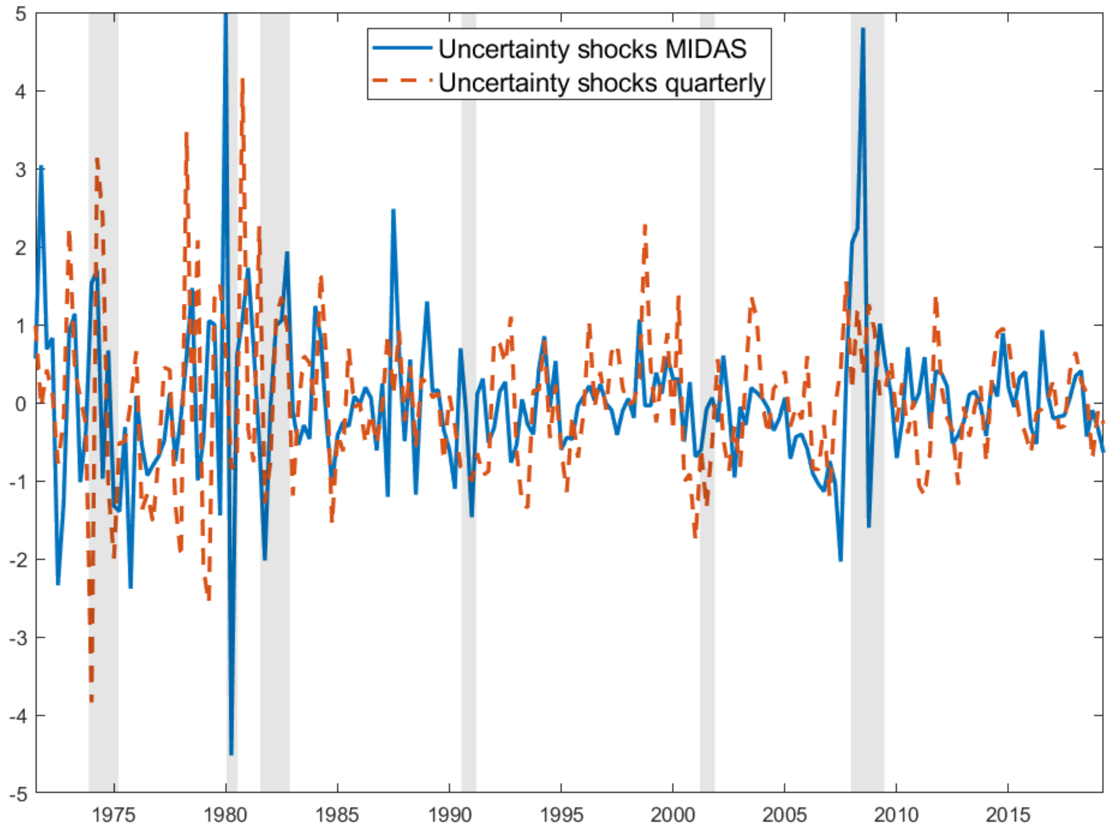

Figure 5: **Unexpected changes in uncertainty**. Unexpected changes in uncertainty in VARs including uncertainty and skewness measures computed with quarterly data-only vs. the MIDAS model.

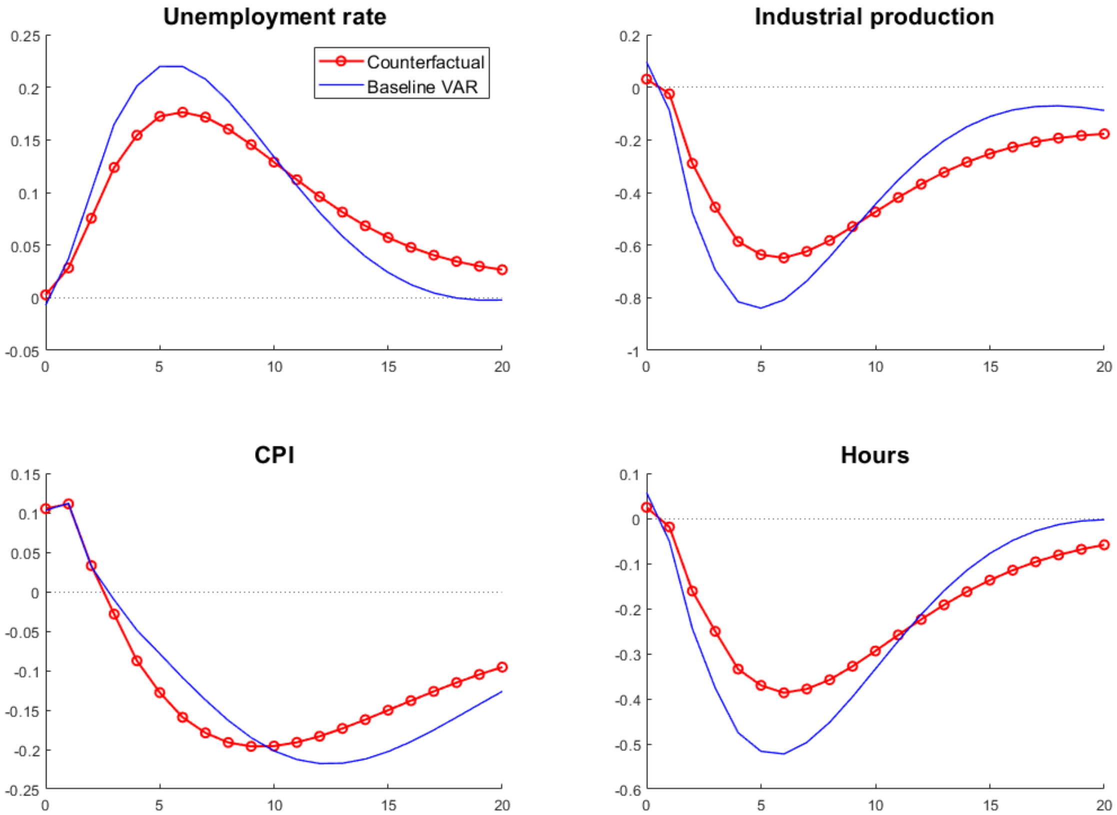

Figure 6: **Counterfactual reaction of real activity to an uncertainty shock: Role of the endogenous response of skewness**. Counterfactual responses consistent with a muted reaction of skewness to an uncertainty shock. Skewness counterfactually kept at zero at all horizons via fictitious shocks.

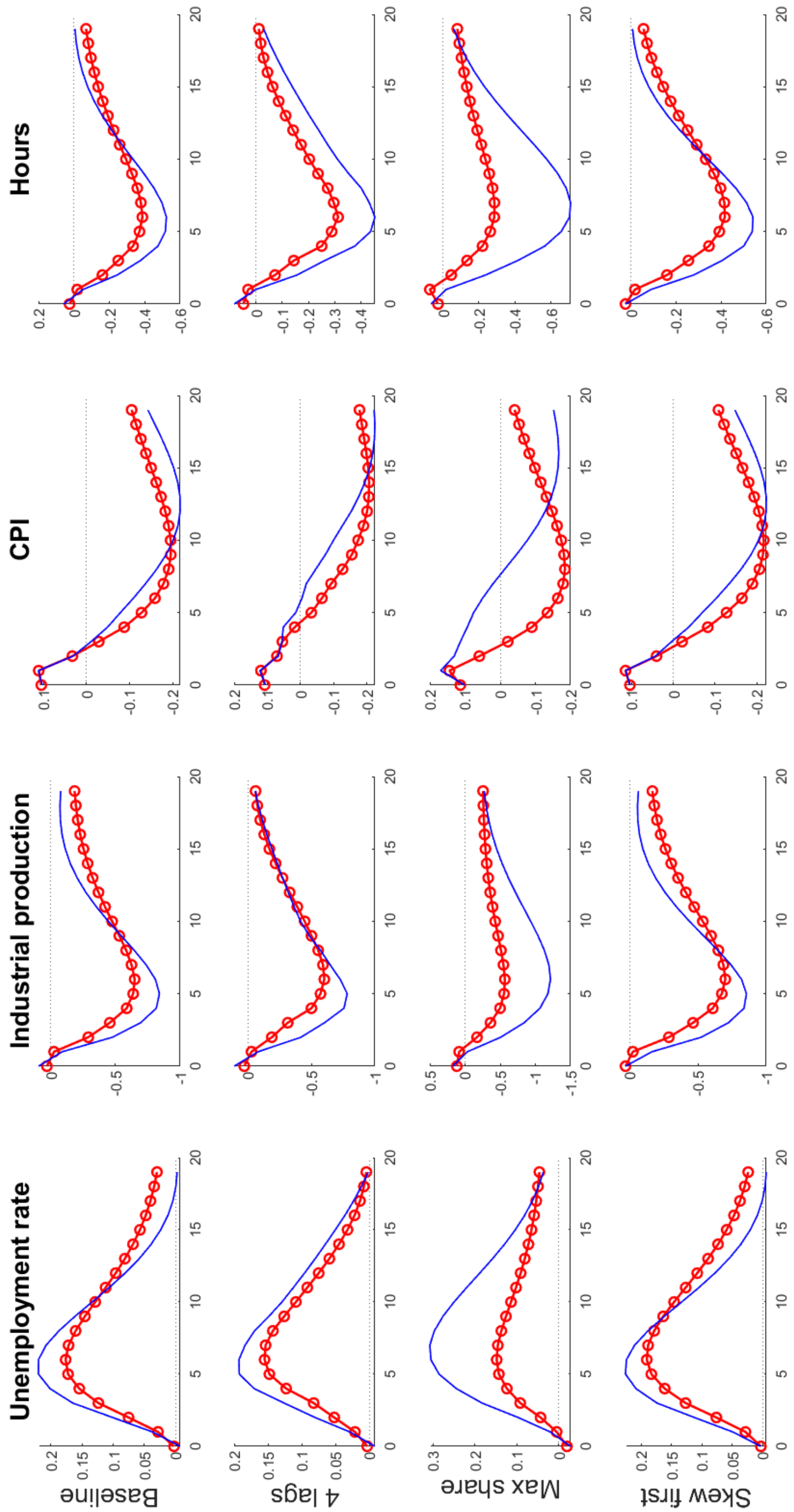

Figure 7: **Counterfactual reaction of real activity to an uncertainty shock: Robustness Checks**. First row: Baseline framework. Second row: Change in lag selection (from 2 to 4 lags). Third row: Identification of the uncertainty and skewness (for the counterfactual) shocks with the max-share strategy à la Uhlig (2003). Fourth row: Skewness ordered before uncertainty in the baseline framework.