Uncertainty as a Predictor of Economic Activity[*]

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Abstract

This paper investigates whether empirical measures of uncertainty are informative about the distribution of future economic activity. I show that the relationship between macroeconomic uncertainty and future GDP growth is nonlinear and asymmetric. Macroeconomic uncertainty predicts downside tail outcomes but is not particularly informative about economic expansions. I also study the relative importance of macroeconomic uncertainty and financial conditions in predicting the distribution of economic activity. Higher macroeconomic uncertainty and tighter financial conditions are both associated with a widening of the left tail of the distribution and thus an increase in downside risks, but macroeconomic uncertainty carries a larger weight in the optimal prediction. Alternative empirical measures of uncertainty, such as economic policy uncertainty and geopolitical risk, do not predict downside risks to the economic outlook, suggesting that it is important to differentiate between measures of uncertainty.

1 Introduction

During the past decade, the United States and many other countries experienced elevated levels of uncertainty. Together with the surprisingly slow pace of recovery from the global financial crisis, this phenomenon sparked renewed interest in the relationship between uncertainty and economic activity. The ensuing debate established that uncertainty behaves countercyclically and rises steeply in recessions. Figure 1 illustrates the relationship between uncertainty and GDP growth in the US for three commonly used proxies for uncertainty: macroeconomic uncertainty, implied stock market volatility, and economic policy uncertainty. For all three measures, the level of uncertainty is markedly higher when GDP growth is in its lowest decile—which typically occurs when the economy is in a recession.[1] This pattern suggests that there is an association between uncertainty and downside tail events.

FIGURE 1: Uncertainty by GDP growth deciles
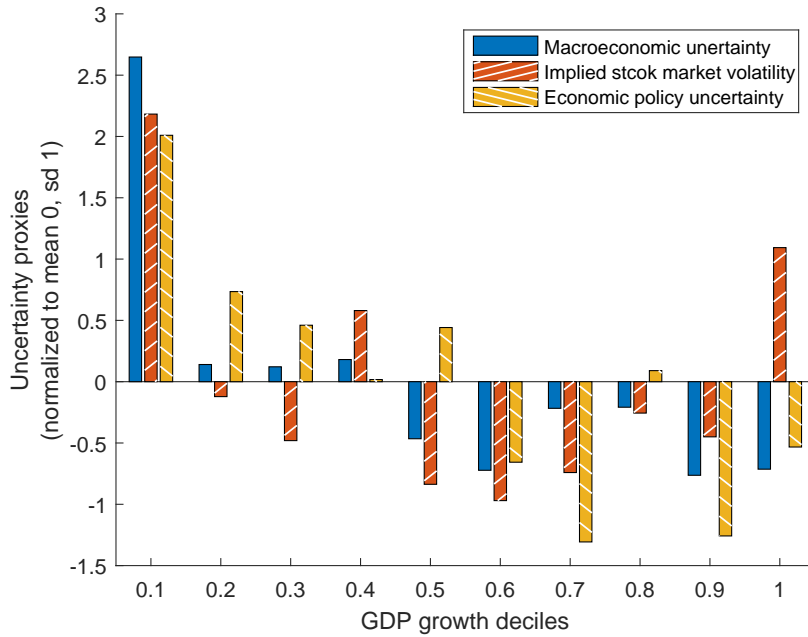
Notes: The sample period covers 1986Q1-2017Q4.

I investigate whether empirical measures of uncertainty are informative about the distribution of future economic activity. First, I employ a novel empirical framework proposed by Adrian et al. (forthcoming) to investigate potential nonlinearities

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[1]GDP growth deciles are calculated for ten bins. That is, the first bin includes any quarter with GDP growth up to -1.00 percent while the second bin includes all quarters during which GDP growth was between -0.99 and 0.81 percent, and so on. The level of uncertainty plotted is the average over uncertainty in each bin.

in the relationship between macroeconomic uncertainty and future economic activity, as measured by GDP growth. I find that the left tail of the conditional distribution of GDP growth is highly responsive to changes in macroeconomic uncertainty whereas the right tail is relatively stable. Macroeconomic uncertainty thus predicts downside outcomes but is not particularly informative about economic expansions. Second, I take into account the findings by Adrian et al. (forthcoming) which reveal similar nonlinearities in relation to financial conditions. To assess the relative importance of macroeconomic uncertainty and financial conditions in predicting the distribution of future growth, I combine the predictive densities in an optimal way. The prediction conditional on macroeconomic uncertainty carries a larger weight in the optimally-combined density of GDP growth than the prediction conditional on financial conditions. Third, I show that different proxies of uncertainty, prima facie, appear to have similar properties. A more formal analysis, however, suggests that neither economic policy uncertainty nor geopolitical risk predict risks to economic activity.

I demonstrate that macroeconomic uncertainty is informative about downside tail outcomes by estimating a set of quantile regressions. Quantile regressions, pioneered by Koenker and Bassett (1978), allow the coefficients to vary across the distribution of the dependent variable. I use them to test whether the relationship between macroeconomic uncertainty and future growth is nonlinear. I find that the relationship between macroeconomic uncertainty and future economic activity is characterized by strong and asymmetric nonlinearities both one quarter ahead and four quarters ahead. Most notably, an increase in macroeconomic uncertainty is associated with a widening of the left tail of the distribution of future growth. Macroeconomic uncertainty is therefore more informative about downside risks to economic activity than about upside risks.

To quantify how informative macroeconomic uncertainty is about risks to economic activity, I predict the full density of future GDP growth, following the framework by Adrian et al. (forthcoming).[2] I measure the strength of the signal from macroeconomic uncertainty as the cumulative probability under the predictive density that falls within one standard deviation of GDP growth around the outturn. For downside tail events, such as the 2007–2009 recession, the predictive density conditional on current growth and macroeconomic uncertainty provides a strong signal relative to the predictive density conditional on current GDP growth only. Macroeconomic uncertainty can also help predict upside risks, although the signal is

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[2]Estimation of the probability density in Adrian et al. (forthcoming) goes back to the prominent work on the skewed t-distribution by Azzalini and Capitanio (2003).

less strong than for downside outcomes. Examining the out-of-sample performance of the predictive densities shows that conditioning on macroeconomic uncertainty leads to prediction gains more than two-thirds of the time.

Next, I show that macroeconomic uncertainty is still informative about downside risks when controlling for financial conditions. Recent evidence shows that there is a nonlinear relationship between the financial conditions index and future GDP growth and that financial conditions predict downside risks to growth (Adrian et al., 2018, forthcoming; IMF, 2017). The coefficients on macroeconomic uncertainty still vary across the distribution of future growth when I include both macroeconomic uncertainty and financial conditions in the estimation of the quantile regressions. A comparison of the predictive densities conditional on macroeconomic uncertainty and conditional on the financial conditions index illustrates that both macroeconomic uncertainty and financial conditions predict downside risks to growth but that the magnitude of predicted downside risks varies across the two predictors. For 2008Q4, for example, macroeconomic uncertainty predicts larger downside risks than financial conditions predict.

To assess the relative importance of macroeconomic uncertainty and financial conditions in predicting the distribution of future GDP growth, I combine the predictive densities following a method developed by Conflitti et al. (2015). The optimal combination of the predictive densities is a weighted average of the individual predictive densities where the weight vector maximizes out-of-sample performance. The optimal weights indicate that macroeconomic uncertainty is, on average, more important than the financial conditions index in predicting future growth. Computing the weights over five-year rolling windows, however, shows that the roles of macroeconomic uncertainty and financial conditions vary across time. For example, while financial conditions played a greater role in the run-up to the 2007–2009 crisis, macroeconomic uncertainty carried a larger weight in the years during and after the crisis.

Finally, I investigate whether my results based on macroeconomic uncertainty generalize to other countries. Quantile regressions of future growth on macroeconomic uncertainty in France, Germany, Italy, and Spain show some evidence of nonlinearities, providing further support for macroeconomic uncertainty as a predictor for downside risks to economic activity. In addition, I examine whether other empirical measures of uncertainty yield similar predictions. I estimate quantile regressions of future growth on economic policy uncertainty for the US and for a larger set of advanced and emerging market economies. These provide no compelling evidence of nonlinearities between economic policy uncertainty and future growth.

Similarly, geopolitical risk does not predict risks to growth in the US and six other economies. Practitioners need to be aware that the various empirical measures of uncertainty might differ in their ability to predict tail outcomes.

This paper relates to two main strands of literature. It contributes to a nascent literature that examines whether uncertainty can predict economic and financial market developments. A recent study by Caldara et al. (2016) compares the performance of a number of uncertainty measures in predicting industrial production and employment. Similarly, Gupta et al. (2014) test whether uncertainty has predictive power for the equity premium. My analysis is different because I allow for nonlinearities by exploring the role of uncertainty for the full conditional distribution of future GDP growth.

Also, there is a long tradition of predicting probability distributions for macroeconomic time series that began with the introduction of the Survey of Professional Forecasters in the US as described in Zarnowitz (1969). A number of studies estimate the conditional distribution of economic activity using quantile regressions (for example, Giglio et al., 2016). My analysis follows closely Adrian et al. (forthcoming) who develop a novel framework for estimating predictive densities and examine the distribution of future real GDP growth conditional on financial conditions. IMF (2017) applies this approach to assess risks to growth associated with financial conditions across a number of advanced and emerging market economies. For the same sample of countries, Adrian et al. (2018) explore the evolution of downside risks due to changes in financial conditions over the prediction horizon. I complement these papers by studying the role of uncertainty, and by analyzing the relative importance of macroeconomic uncertainty and financial conditions in predicting the distribution of economic activity.

The remainder of this paper is organized as follows. In Section 2, I describe the data and present a set of stylized facts about macroeconomic uncertainty and future growth. Section 3 lays out the empirical strategy and presents the baseline results. Section 4 studies the relative importance of macroeconomic uncertainty and financial conditions in predicting the density of GDP growth. In Section 5, I consider alternative measures of uncertainty. Section 6 concludes and discusses policy implications.

2 Data and Stylized Facts

Uncertainty is a latent variable that cannot be observed directly. A multitude of proxy measures have been proposed, relying predominantly on measures of uncer-

tainty that track the frequency of keywords in newspaper articles (for example, Baker et al., 2016; Husted et al., 2017; Caldara and Iacoviello, 2018), measures based on forecast errors (among others, Jurado et al., 2015; Rossi and Sekhposyan, 2015), and measures of implied or realized financial market volatility (for example, Bloom et al., 2007; Baker and Bloom, 2013; Gilchrist et al., 2014).

I use the measure of macroeconomic uncertainty (MACROU) proposed by Jurado et al. (2015) which is a comprehensive measure of uncertainty that encompasses a wealth of information about the economy.[3] MACROU is defined as the expected conditional volatility of the unforecastable component of the economy. Based on a stochastic volatility model, uncertainty is computed for 132 monthly series capturing the macroeconomic environment. The MACROU index is a simple average of the individual uncertainty measures.[4] I took averages across the months within each quarter to transform the monthly index into a quarterly measure.[5]

To study the relative roles of uncertainty and financial conditions, I collected the Chicago Fed national financial conditions index (FCI) from the Federal Reserve Bank of St. Louis. The FCI summarizes 105 measures of financial activity that capture risk, credit, and leverage in a single common component. Positive values of the FCI are associated with tighter than average financial conditions. I also took data on quarterly real GDP growth at an annualized rate from the Federal Reserve Bank of St. Louis.[6] Table A.1 in Appendix A reports the summary statistics for GDP growth, MACROU, and the FCI. The sample period covers 1971Q1–2017Q4.

To investigate the properties of MACROU beyond the US, I obtained an equivalent measure for France, Germany, Italy, and Spain, the largest economies in the euro area. I obtained the German MACROU series covering 1991Q2–2017Q4 from Grimme and Stöckli (2018). The series for France, Italy, and Spain, all over 1996Q3–2015Q4, were taken from Meinen and Roehe (2017). The construction of these MACROU indexes follows the method proposed by Jurado et al. (2015) and is based on a set of 114, 102, 108, and 110 monthly macroeconomic series for France, Germany, Italy, and Spain, respectively.

I also collected data on two alternative empirical measures of uncertainty. The first is the economic policy uncertainty (EPU) index which was developed by Baker et al. (2016) and is available for a number of advanced and emerging market

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[3] Available here.

[4] Jurado et al. (2015) combine a macroeconomic and financial dataset, containing 132 and 147 series, respectively, to form forecasting factors for the 132 macroeconomic series.

[5] I also transform all other series that were obtained monthly/weekly to quarterly series by averaging over the months/weeks of the quarter.

[6] Available here.

economies. It measures uncertainty around economic policy based on newspaper coverage. To capture uncertainty, a newspaper article must contain keywords from three categories covering uncertainty, the economy, and policy. I collected quarterly data on EPU for the US and a set of advanced and emerging market economies over 1985Q1–2017Q4 from Thomson Reuters Datastream.[7] Due to limited data availability, the EPU sample is unbalanced. Table A.2 in Appendix A lists the available sample period for each country.

The second alternative proxy is the geopolitical risk (GPR) index which was proposed by Caldara and Iacoviello (2018). The GPR index, similarly to the EPU index, is constructed on the basis of keyword counts in newspaper articles. It measures the risk that geopolitical events materialize and that existing geopolitical events escalate. Caldara and Iacoviello (2018) define geopolitical events as threats and acts related to nuclear perils, terrorist attacks, wars, and general geopolitical tensions. I obtained the global measures of the GPR index—which can be viewed as a measure relevant for North America and the UK—as well as country-specific GPR measures over 1985Q1–2017Q4.[8]

Finally, I collected data on quarterly real GDP growth for the set of advanced and emerging economies from the OECD.Stat database and transformed them into growth rates at an annualized rate.[9] The GDP growth rates for Brazil and China were taken from Mohaddes and Raissi (2018).

Next, I document two stylized facts of uncertainty and GDP growth over the business cycle. First, as suggested in Section 1, MACROU behaves countercyclically and rises steeply in recessions. Figure 2 shows the evolution of MACROU and GDP growth over 1971Q1–2017Q4 together with NBER-dated recessions. MACROU tends to increase (decrease) when GDP growth decreases (increases). We observe spikes of MACROU during recessions. These were particularly large during the 1980 and the 2007–2009 recessions. In 2008Q4 MACROU reached a peak and then declined to its pre-crisis level.

Second, the relationship between MACROU and GDP growth appears to be nonlinear across the distribution of GDP growth. Figure 3 illustrates MACROU by GDP growth deciles. GDP growth deciles are calculated for three bins over

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[7]For the US, two alternative versions of the EPU index are available. The first is an index that, in addition to the news-based component, also captures federal tax code provisions expiring in the future and disagreement among professional forecasters. The second is a historical index that goes back further in time and is based on a reduced number of newspapers. For comparability of the EPU index across countries, I use the news-based index for the US.

[8]Country-specific GPR indexes are available for a large number of countries. I obtained the data for those countries that are also in the EPU sample which are Brazil, China, India, Korea, Mexico, and Russia.

[9]Available here.

1971Q1–2017Q4. The first bin includes any quarter with GDP growth in the first decile, that is, up to -1 percent. The second bin includes all quarters during which GDP growth was between the second decile and the median, i.e. between -0.99 and 3 percent while the third bin includes all quarters for which GDP growth was above the median.

The fitted lines indicate that the relationship between MACROU and GDP growth is highly negative when GDP growth is in its lowest decile. For other poor growth outcomes, when GDP growth is above the first decile and less than or equal to the median, the correlation is still negative, but somewhat weaker. When GDP growth is above the median, the relationship between MACROU and growth is slightly positive. These two stylized facts show that the association between MACROU and GDP growth is overall negative. This relationship is much stronger when growth is very low. In the next section, I formally investigate how the distribution of future GDP growth varies with fluctuations in uncertainty.

3 Uncertainty and Future GDP Growth

This section shows that MACROU predicts downside risks to future economic activity. Employing the empirical framework proposed by Adrian et al. (forthcoming), I start by estimating quantile regressions. I then recover the predictive density of future GDP growth from the conditional quantile function and examine the out-of-sample performance of my predictions.

3.1 Baseline Estimation: Allowing for Nonlinearities

Quantile regressions characterize the relationship between regressors and the dependent variable over the entire distribution of the dependent variable. They thus provide a suitable method to explore potential nonlinearities in the conditional relationship between MACROU and future GDP growth.[10] For any $0 < \tau < 1$, $F^{-1}(\tau) = \inf\{x : F(x) \geq \tau\}$ is defined as the τth quantile of a real-valued random variable X. For a given quantile, τ, I estimate

$$y_{t+h,\tau} = \beta_\tau x_t + \varepsilon_{t,\tau} \tag{1}$$

where $y_{t+h,\tau}$ denotes the τth conditional quantile of annualized average GDP growth between time t and $t + h$ and $h \geq 1$ is the prediction horizon. In the baseline

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[10]For a comprehensive overview of quantile regressions see Koenker (2005).

specification, equation (1), x_t is a vector of conditioning variables including an intercept, current GDP growth, and MACROU.

The quantile regression estimator chooses β_τ to minimize the asymmetrically-weighted sum of absolute residuals

$$\hat{\beta}_\tau = \min_{\beta_\tau} \sum_{t}^{T-h} \omega_t(\tau) \mid y_{t+h} - \beta x_t \mid \tag{2}$$

with weights

$$\omega_t(\tau) = \begin{cases} \tau & \text{if } y_{t+h} \geq \beta x_t \\ (1-\tau) & \text{if } y_{t+h} < \beta x_t. \end{cases} \tag{3}$$

The asymmetric loss function assigns differing weights to positive and negative residuals. For example, for any quantile above the median, an underestimate (positive residual) is more costly than an overestimate (negative residual). This asymmetric loss function yields the conditional quantile as the solution (Koenker and Bassett, 1978; Koenker and Hallock, 2001).

Figure 4 presents the baseline results. It illustrates the coefficient estimates on MACROU from the quantile regressions across the conditional distribution of future growth. The 90/68 percent confidence bands indicate whether the coefficient estimates are significantly different from a linear model. The vertical dashed line shows the ordinary least squares estimate for comparison. Panel (a) presents the coefficients on MACROU for one-quarter-ahead predictions while panel (b) illustrates the coefficients at the four-quarter horizon.

There are pronounced nonlinearities between MACROU and future growth at both prediction horizons. One quarter ahead, the coefficients on MACROU are significantly different from a linear model at both tails of the distribution. An increase in MACROU predicts a large decline in the lower quantiles of future GDP growth and a small increase in the upper quantiles of future growth, suggesting that the relationship between MACROU and future growth is not only nonlinear but also asymmetric. The results are similar at the four-quarter-ahead horizon. The coefficients on current GDP growth, in contrast, are relatively stable across the different quantiles but show some nonlinearities at the upper tail of the one-quarter-ahead predictions (see Figure B.1 in Appendix B).

I proceed by fitting the predicted conditional quantiles of future GDP growth. To discuss the link between MACROU and risks to growth, I focus on the 5th and 95th conditional quantiles which are informative about downside and upside

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risks, respectively. I also show the median (the 50th quantile) as a measure of the central tendency. Figure 5 depicts MACROU and the predicted quantiles of future growth. Both one quarter ahead (panel (a)) and four quarters ahead (panel (b)), the predictions for the 95th and 50th quantiles are relatively stable over time. The predictions for the 5th conditional quantile, in contrast, vary strongly across time. Increases in MACROU are associated with a widening of the left tail, illustrating that MACROU predicts downside risks to economic activity. Overall, these results suggest that MACROU is an asymmetric and nonlinear phenomenon.

3.2 Predictive Distributions of Growth

Having shown predicted GDP growth for selected quantiles over time, I now recover the entire predictive density of future growth at specific points in time. This allows me to assess the strength of the signal for risks to growth from MACROU.

The predicted values from the quantile regressions in equation (1) provide a consistent estimate of the conditional quantile function—i.e. the inverse cumulative distribution function—of future GDP growth (Koenker and Bassett, 1978). Following the framework proposed by Adrian et al. (forthcoming), the probability density function can be recovered in two steps. In the first step, the skewed t-distribution, which was developed by Azzalini and Capitanio (2003), is fitted to smooth the quantile function, $\hat{Q}_{t+h,\tau}$. The skewed t-distribution depends on four parameters: mean (μ), volatility (σ), skewness (θ), and kurtosis (ν). These four parameters are chosen to minimize the squared loss between the estimated quantile function and the inverse of the cumulative distribution function of the skewed t-distribution for the 5th, 25th, 50th, and 75th quantiles

$$\{\hat{\mu}_{t+h}, \hat{\sigma}_{t+h}, \hat{\theta}_{t+h}, \hat{\nu}_{t+h}, \} = \min_{\mu,\sigma,\theta,\nu} \sum_{\tau} \left(\hat{Q}_{y_{t+h}|x_t,\tau} - F_{\tau}^{-1}(\mu,\sigma,\theta,\nu) \right)^2. \qquad (4)$$

In the second step, the probability density is recovered by shaping the probability density function of the Student t-distribution, $t(\cdot)$, by its cumulative distribution function, $T(\cdot)$, and a scale parameter, θ[11]

$$\hat{f}_{t+h}(y; \hat{\mu}, \hat{\sigma}, \hat{\theta}, \hat{\nu}) = \frac{2}{\hat{\sigma}} t\left(\frac{y-\hat{\mu}}{\hat{\sigma}}; \nu \right) T\left(\hat{\theta} \frac{y-\hat{\mu}}{\hat{\sigma}} \sqrt{\frac{\hat{\nu}+1}{\hat{\nu}+\left(\frac{y-\hat{\mu}}{\hat{\sigma}}\right)^2}}; \nu+1 \right). \qquad (5)$$

I predict the density of future growth for three quarters of my sample: 2008Q4 which is the quarter with the worst performance of the US economy in its recent

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[11] I drop the time subscripts from μ, σ, θ, and ν for convenience.

history and represents a downside risk scenario, 2013Q3 which can be considered a typical quarter with GDP growth close to the historical median growth rate in the sample, and 2014Q3 which was the quarter with the strongest growth performance in the post-crisis period and thus illustrates an upside scenario. Figure 6 presents the predictive densities for 2008Q4. Panel (a) shows the one-quarter-ahead predictions based on two specifications: the density conditional on current GDP growth only and the density conditional on current GDP growth and MACROU which is the baseline specified in equation (1). The latter is characterized by a left tail that is shifted out further and assigns a larger probability to the outturn as indicated by the vertical line. In addition, the mode of the predictive density conditional on GDP growth and MACROU is closer to the outturn than the mode of the density conditional on growth only. Four quarters ahead (panel (b)), conditioning on MACROU also shifts the predictive density of future growth to the left. This outward shift is smaller than it is for the one-quarter-ahead prediction, however.

To quantify how informative MACROU is about risks to growth, I compute the cumulative probability within one standard deviation of GDP growth around the outturn.[12] Panels (c) and (d) of Figure 6 illustrate the signal from the predictive density conditional on current growth and MACROU (blue shaded area) and the signal from the predictive density conditional on current growth only (red shaded area).[13] One quarter ahead, the cumulative probability around the outturn of the former is 5.9 times the cumulative probability of the latter. This suggests that MACROU provides a strong signal for downside risks to growth.

Four quarters ahead, the cumulative probability around the outturn of the probability density that conditions on current growth and MACROU is 1.3 times larger than the one of the probability density conditional on current GDP growth only. In other periods, four-quarter-ahead estimates provide an even stronger signal of downside risks to growth. In 2009Q2 and 2009Q3, for example, the ratio of the cumulative probability within one standard deviation around the outturn of the density conditional on current growth and MACROU over the density conditional on current growth only is 3.3 and 5.6, respectively (Figure B.2 in Appendix B). Moreover, for 2008Q4, the two- and three-quarter-ahead predictions conditional on MACROU provide a signal for downside risks that is 3 and 3.7 times stronger, respectively, than the signal from the prediction conditional on current growth only (Figure B.3 in Appendix B).

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[12]The unconditional standard deviation of one-quarter-ahead growth is 3.3 while it is 2.2 for four-quarter-ahead growth. I add $\pm\frac{1}{2}$ standard deviations to the outturn to compute the cumulative probability within one standard deviation around the outturn.

[13]Observe that the two shaded areas are partially overlapping.

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Figure 7 shows the predictive densities for 2013Q3. At both prediction horizons, the density conditional on current GDP growth and MACROU does not show the widening of the left tail that it exhibits during the recession. That is, MACROU does not predict downside risks to growth in normal times, and correctly so. The ratio of the cumulative probability within one standard deviation of growth around the outturn of the density that conditions on MACROU over the cumulative probability of the density conditional on current growth only is 1.5 one quarter ahead and 0.9 four quarters ahead. This raises the question whether MACROU predicts upside risks to growth. In 2014Q3 (Figure 8), which is currently the quarter with the highest growth rate during the current economic expansion, these ratios amount to 1.4 and 1.3 one and four quarters ahead, respectively.

Hence, incorporating MACROU in the estimation is useful for detecting downside risks and can help to increase the accuracy of predictions in good times. Nonetheless, the signal from MACROU—compared to the signal from current GDP growth only—is considerably stronger for adverse future economic outcomes. This suggests that MACROU is particularly suited to predicting downside events.

3.3 Out-of-Sample Evidence

In this section, I explore the out-of-sample performance of the model. The parameters are estimated recursively with an initial estimation sample that comprises 1971Q1–1990Q4 and increases by one quarter during each iteration.

I begin the out-of-sample analysis by comparing in-sample and out-of-sample predictions for the baseline specification that conditions on current GDP growth and MACROU. Figure 9 shows that the 5th, 50th, and 95th quantiles of out-of-sample predicted GDP growth are very similar to the in-sample predictions both one quarter ahead and four quarters ahead. The left tail of the conditional distribution, the 5th quantile, predicts downside risk to growth even if estimated in pseudo real-time.

To assess the out-of-sample accuracy of the predictive densities conditional on current GDP growth only and conditional on current GDP growth and MACROU, I compare the predictive scores across the two densities. The predictive score is computed by evaluating the predictive density at the outturn of future GDP growth, $\hat{f}_{t+h}(y_{t+h}; \hat{\mu}_{t+h}, \hat{\sigma}_{t+h}, \hat{\nu}_{t+h}, \hat{\theta}_{t+h})$. A higher score thus implies that the prediction is more accurate. Figure 10 illustrates that the predictive score of the density conditional on both current growth and MACROU is higher than the predictive score of the density conditional on GDP growth only during 69 percent and 66 percent of the out-of-sample period one quarter ahead (panel (a)) and four quarters ahead (panel (b)), respectively.

4 Uncertainty versus Financial Conditions

Adrian et al. (2018, forthcoming) and IMF (2017) show that a tightening of financial conditions predicts downside risks to growth. In this section, I take into account the role of financial conditions. Following a comparison of the results conditional on MACROU and the FCI, I combine the predictive densities using optimal weights.

4.1 Role of Financial Conditions

MACROU and the FCI are highly correlated; over the sample period from 1971Q1–2017Q4, the correlation coefficient is approximately 0.8. Both MACROU and the FCI tend to increase in recessions (Figure 11). So is the signal for downside risks to growth driven by one of these two series, and how do the individual predictors compare?

I re-estimate equation (1) where x_t now includes an intercept, current GDP growth, MACROU, and the FCI. Figure 12 illustrates the coefficients on MACROU and the FCI. For comparison, I also show the coefficients on MACROU and the FCI when only one of them is included in the estimation. Note that the confidence bands shown are the ones for the model including both MACROU and the FCI. One quarter ahead (panel (a)), the relationship between future growth and MACROU still displays a nonlinear pattern. At the lower quantiles of the distribution, however, the coefficients are smaller in magnitude than the coefficients in the regression without the FCI. Moreover, the confidence bands are wider (see Figure 4) which is expected given the collinearity between MACROU and the FCI. At the four-quarter prediction horizon (panel (c)), the coefficients on MACROU remain similar when controlling for the FCI but are—with the exception of the very lower quantile and the very upper quantile—not significantly different from a linear model.

The nonlinearities between future GDP growth and the FCI become less significant and considerably weaker for the lower quantiles of the distribution when controlling for MACROU (panels (b) and (c)). As above, the confidence bands are somewhat wider, reflecting the collinearity between MACROU and the FCI (see Figure B.4 in Appendix B for the confidence bands when conditioning on current GDP growth and the FCI only). Hence, while both series individually exhibit a nonlinear relationship with future growth, it is not evident that these nonlinearities are driven by one series only. Nonetheless, the coefficients on MACROU display a relatively stronger nonlinear pattern. This might suggest that MACROU has larger explanatory power for future downside tail outcomes.

Next, I explore how the predictive densities based on MACROU and the FCI

compare for 2008Q4. Figure 13 depicts the predictive density conditional on current GDP growth, MACROU, and the FCI together with the densities that condition on MACROU and the FCI separately. Panel (a) illustrates the one-quarter-ahead predictions. Two observations are noteworthy. First, the predictive density conditional on current growth and MACROU lies to the left of the density conditional on current growth and the FCI. MACROU predicts larger downside risks by assigning a higher probability to growth outcomes around the outturn. Second, the predictive density conditional on current growth, MACROU, and the FCI is basically indistinguishable from the density conditioning on current growth and MACROU only. Hence, MACROU predicts downside risks to growth even when controlling for the FCI. Four quarters ahead (panel (b)), all three densities are similar and assign roughly equal probabilities to the outturn.

During calm economic times, such as in 2013Q3 (Figure 14), and during economic upswings, such as in 2014Q3 (Figure 15), neither MACROU nor the FCI signal downside risks to growth. The conditional densities on MACROU and the FCI assign similar probabilities to the outturn at both prediction horizons. Overall, the signal for upside growth outcomes around the outturn tends to be slightly stronger for MACROU than for the FCI.

4.2 Optimal Combination of Predictive Densities

Given that both MACROU and the FCI individually predict downside risks to growth, an important question is how the information in both series can be best exploited. I thus combine the predictive densities presented above in an optimal way and show that the relative importance of MACROU and the FCI varies across time.

To find the optimal combination of the predictive densities, I employ an iterative algorithm developed by Conflitti et al. (2015).[14] Let $\hat{f}_{t+h}(\cdot)$ denote the optimally combined density which is a weighted average of N individual density forecasts

$$\hat{f}_{t+h}(\cdot) = \sum_{i=1}^{N} \omega_i \hat{f}_{i,t+h|t}(\cdot), \qquad i = 1, ..., N \tag{6}$$

where the optimal combination weights are restricted to be nonnegative, $\omega_i \geq 0$, and to sum to one, $\sum_{i=1}^{N} \omega_i = 1$. These restrictions ensure that the combined density

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[14]For other papers that study similar methods to combine density forecasts see, for example, Geweke and Amisano (2011) and Hall and Mitchell (2007). The approach proposed by Conflitti et al. (2015) departs from this earlier literature by allowing the number of densities that are combined to be large.

satisfies the properties of a probability density function.

The optimal vector of weights, $\boldsymbol{\omega}$, maximizes the out-of-sample performance of the combined probability density as measured by the log predictive score

$$\phi(\boldsymbol{\omega}) = \frac{1}{T-h} \sum_{t=1}^{T-h} \ln \hat{f}_{t+h}(y_{t+h}). \tag{7}$$

The iterative algorithm computes the optimal weights based on a minorization-maximization strategy. Conflitti et al. (2015) show that the optimization problem simplifies to

$$\omega_i^{(k+1)} = \omega_i^{(k)} \frac{1}{T-h} \sum_{t=1}^{T-h} \frac{\hat{f}_{i,t+h}(y_{t+h})}{\sum_{l=1}^{N} \hat{f}_{l,t+h}(y_{t+h}) \omega_l^{(k)}}. \tag{8}$$

I simultaneously estimate the optimal weights associated with each predictive density by running equation (8) until the convergence criteria of $\omega_i^{(k+1)} - \omega_i^{(k)} < 0.00001$ is met for all ω_i.

I now estimate the optimal weight for the three predictive densities that condition on (i) current growth and MACROU, (ii) current growth and the FCI, and (iii) current growth only. As in the previous section, the out-of-sample predictions are estimated recursively starting in 1991Q1 and 1991Q4 for the one-quarter-ahead and four-quarter-ahead horizon, respectively.

The results presented in Table 1 show that MACROU plays an important role in predicting the density of future GDP growth at both prediction horizons. One quarter ahead, the density conditioning on current growth and MACROU accounts for more than half of the optimally-combined prediction. Yet, the density that conditions on current growth and the FCI also has a relatively large weight of approximately 0.48. At the four-quarter-ahead horizon, almost two-thirds of the optimal combination are accounted for by the density conditioning on MACROU, suggesting that MACROU plays an even more important role at this slightly longer horizon.

Figure 16 presents the optimally-combined densities for 2008Q4. The combined density is a weighted average of the original three densities where the weights are taken from Table 1. At both prediction horizons, the optimally-combined density yields an improvement over the density conditioning on the FCI. However, the one-quarter-ahead predictions (panel (a)) show that the density which conditions on current growth and MACROU assigns a higher probability to the outturn than the optimally-combined density. Hence, while it is optimal to combine the densities with

the overall weights from Table 1 over the entire out-of-sample period, the individual predictive densities might be more accurate for a particular point in time.

To investigate whether the relative importance of MACROU and the FCI varies across time, I estimate the optimal combination weights for five-year rolling windows. Panel (a) of Figure 17 shows the optimal weights for one-quarter-ahead predictions. The weights for each predictive density vary strongly across time, or more precisely, across states of the economy. In the mid-to-late nineties—a time period characterized by the 1997 Asian and 1998 Russian financial crises as well as the 1998 failure of Long-Term Capital Management—the density conditioning on current growth and the FCI carried a large weight in the optimal prediction. Similarly, the weight of the FCI increased strongly in the run-up to the 2007–2009 global financial crisis. In the aftermath of the crisis, however, the weight for the FCI steadily declined while MACROU carried a relatively large weight.

At the four-quarter-ahead horizon shown in panel (b) there is less variation across time. The density that conditions on current growth and MACROU appears to be relatively important in predicting the density of future growth in the 2000s. During the past decade, however, that weight has been declining and the FCI and current growth only have become more important.

How to compute the optimal weights in practice remains an area for further research. For example, computing the weights based on past periods that have shown the same developments as the current period would be a possibility to generate weights that are customized to the state of the economy.

5   Alternative Measures of Uncertainty

This section explores whether MACROU predicts risks to growth in France, Germany, Italy, and Spain. I also compare the properties of economic policy uncertainty (EPU) and geopolitical risk (GPR) to those of MACROU and investigate whether these alternative measures of uncertainty predict downside risks to growth in the US as well as in a larger set of advanced and emerging market economies.

5.1   Macroeconomic Uncertainty in Europe

To explore whether the US results generalize to other economies, I test for nonlinearities between MACROU and future GDP growth in France, Germany, Italy, and Spain. MACROU indexes constructed in line with Jurado et al. (2015) are available for those countries albeit for a considerably shorter period. With this caveat in

mind, I re-estimate equation (1) separately for each of the four economies where y_t refers to annualized GDP growth and x_t includes a constant, current GDP growth, and MACROU.

Figure 18 shows the one-quarter-ahead coefficients on MACROU for France, Germany, Italy, and Spain. The coefficients show some nonlinearities across the distribution of future GDP growth in all four economies. While the coefficients are significantly different from a linear model mostly at the right tail, they also display a nonlinear pattern at the left tail. The relatively wide confidence bands might reflect the short sample for the MACROU series for those economies. Figure 19 presents the four-quarter-ahead estimates. Again, the coefficients suggest that the relationship between MACROU and future growth is nonlinear.

During the past crisis, these four European countries experienced the largest decline in GDP growth in 2009Q1. Figure 20 illustrates that MACROU also provides a strong signal for this downside scenario. The signal from the density conditional on current growth and MACROU (blue shaded area) is approximately 3 times stronger than the signal from current growth only (red shaded area) in France and Germany. It is also more than twice as strong in Spain. In Italy, the two densities assign a similar probability to outcomes around the outturn. These results provide further evidence that MACROU predicts downside risks to economic activity. Constructing uncertainty measures that capture MACROU both over a longer period of time and in economies other than the ones presented here is promising insights into the dynamics between MACROU and future growth in an even larger sample of countries.

5.2 Economic Policy Uncertainty and Future GDP Growth

An alternative proxy for uncertainty that has attracted a lot of attention recently is EPU. At first glance, EPU appears to have similar properties to MACROU. Figure 1 illustrates that EPU is elevated when economic growth is in the lowest decile. The level of EPU is considerably lower for the other deciles of growth, particularly when growth is above the median. Overall, EPU and MACROU display very similar patterns across the deciles of GDP growth.

To more formally investigate the relationship between EPU and future economic growth, I re-estimate equation (1) where the vector of conditioning variables, x_t, now comprises a constant, current GDP growth and EPU. Figure 21 presents the results. Both one and four quarters ahead, the relationship between future growth and EPU does not exhibit significant nonlinearities. Hence, the nonlinearities between MACROU and future growth are specific to MACROU. In contrast to what Figure

1 might have suggested, EPU does not predict downside risks to future growth. The predictive densities conditional on current growth and EPU further support this conclusion (Figure B.5 in Appendix B).[15,16]

As data on EPU are available for a number of economies, I explore the relationship between EPU and future growth in a sample of twelve advanced economies and six emerging market economies.[17] Figure 22 displays the coefficients on EPU for one-quarter-ahead predictions of GDP growth in advanced economies. Across the majority of countries, the distribution of coefficients on MACROU is relatively flat and not different from a linear model. Exceptions are Italy (panel (f)) for which some coefficients are statistically different from a linear model at the right tail and Japan (panel (g)) which displays a significantly nonlinear relationship between EPU and future growth at the very left tail. Among the emerging market economies shown in Figure 23, India shows some nonlinearities at the very left and very right tail of the distribution of future growth (panel (d)) while for Russia EPU is significantly different from a linear model for the fifth quantile of future GDP growth (panel (f)). Overall, there is no compelling evidence of a formal nonlinear relationship between EPU and future growth. This finding suggests that it is important to differentiate between the various proxies available for uncertainty.

5.3 Geopolitical Risk and Future GDP Growth

Finally, I examine whether GPR predicts risks to growth in the US and in six other economies.[18] Figure 24 shows the global GPR index—which can be considered a measure highly relevant to the US—by GDP growth deciles along with MACROU and EPU. As discussed above, MACROU and EPU are much higher when growth is in its lowest decile. This is not the case for the GPR index. Nonetheless, GPR tends to be higher, on average, when growth is below the median.

I again proceed by re-estimating equation (1) conditional on a constant, current

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[15]The results are qualitatively unchanged when I replace the news-based EPU index with the three-components EPU index (over 1985Q1–2017Q4) or with the historical EPU index (over 1971Q1–2017Q4).

[16]The results also suggest that the coefficient on EPU in a linear model is not statistically different from zero. This finding contrasts with the negative association between EPU and economic activity estimated by Baker et al. (2016) and Biljanovska et al. (2017), among others, and can be explained by the difference in the regression specifications.

[17]Australia, Canada, France, Germany, Ireland, Italy, Japan, Korea, the Netherlands, Spain, the UK, and the US are categorized as advanced economies whereas Brazil, Chile, China, India, Mexico, and Russia are considered emerging market economies. The sample periods vary across countries and are described in more detail in Table A.2 in Appendix A.

[18]These are also part of the EPU sample and include Brazil, China, India, Korea, Mexico, and Russia.

GDP growth, and GPR. Figure 25 presents the coefficients on the GPR index for the US. At both prediction horizons, the coefficients on GPR are not significantly different from a linear model across the distribution of future growth. Intriguingly, however, there is a weak nonlinear pattern which—although not significant—suggests that an increase in GPR is associated with an increase in the lower quantiles of one-quarter-ahead growth and a decline in the upper quantiles (panel(a)). Four quarters ahead (panel (b)), the coefficients are positive across the entire distribution of future growth and also larger in magnitude for the lower quantiles of the future GDP growth distribution. As expected, the predictive densities for 2008Q4 and 2014Q3 conditional on current growth and GPR are very similar to the density conditional on current growth only. This confirms that the GPR index predicts neither downside risks nor upside risks to economic activity (Figure B.6 in Appendix B).

Similarly, the relationship between GPR and future GDP growth is relatively stable across the distribution of future growth in the other six economies in my sample (Figure 26). The coefficients show a weak nonlinear pattern across the distribution of future growth in India (panel (c)), Korea (panel (d)), and Mexico (panel(e)) but are not significantly different from a linear model. This result provides further evidence that GPR is not suitable as a predictor of risks to economic activity.

6 Conclusion

Elevated levels of uncertainty observed in the US and in many other countries during the past decade have generated a renewed interest in the relationship between uncertainty and economic activity. In this paper I investigate whether uncertainty is informative about the distribution of future GDP growth. My findings suggest that periods of high uncertainty coincide with a widening of the left tail of the distribution of predicted growth. The right tail of the distribution does not vary strongly with fluctuations in uncertainty. Macroeconomic uncertainty thus predicts downside risks to economic activity but is less informative about upside risks.

Combining predictive densities in an optimal way shows that while both macroeconomic uncertainty and the financial conditions index help in predicting the distribution of future growth, macroeconomic uncertainty carries, on average, a larger weight in the optimal prediction. However, the optimal weights vary across time, suggesting that the role of each series in predicting growth depends on the economic circumstances. In addition, the findings on macroeconomic uncertainty do not nec-

essarily generalize to other proxies for uncertainty. Economic policy uncertainty and geopolitical risk do not predict downside risks to growth.

These findings have important policy implications. Predicting the full density of growth is more informative than a simple point prediction; it helps to understand risks around the central tendency and enables policymakers to predict downside risks to the economic outlook. A better understanding of downside risks allows for coordinated action to mitigate the severity of the downturn. A range of predicted future growth outcomes can be used to assess the overall economic outlook and can strengthen macroeconomic surveillance in a number of areas. For example, the predictive density of future growth outcomes could be used to define alternative scenarios for assessing the sustainability of the fiscal balance and public debt. Similarly, it could inform the choice of adverse macro scenarios for stress testing. Furthermore, density predictions are not confined to GDP growth and can be used to assess risks to other economic and financial series too.

In addition, the results suggest that taking macroeconomic uncertainty into account can improve economic monitoring. Macroeconomic uncertainty provides a strong signal for downside risks to economic activity and yields prediction gains beyond those from financial conditions. As the relative importance of macroeconomic uncertainty and financial conditions varies with economic circumstances, optimally combining predictive densities can be informative for policymakers.

The results provide motivation for future work. First, an important task for future research is constructing measures of macroeconomic uncertainty for a larger set of countries and investigating whether macroeconomic uncertainty predicts downside risks in those economies as suggested by the results for France, Germany, Italy, and Spain. Second, an extension of this paper should employ real-time measures of macroeconomic uncertainty and financial conditions. The time series used in this analysis are based on revised data and the full sample rather than the observations available in each quarter of the sample in real time. Third, practitioners could benefit from a better understanding of which predictor matters most in different states of the economy. In which circumstances does the predictive power of macroeconomic uncertainty dominate that of financial conditions and vice versa? Last, a key question not addressed in this paper is why the various proxies for uncertainty differ in their ability to predict risks to growth. The answer could be in the measurement of uncertainty or in the specific type of uncertainty captured by the different proxies.

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Figures

FIGURE 2: MACROU and GDP growth over the business cycle
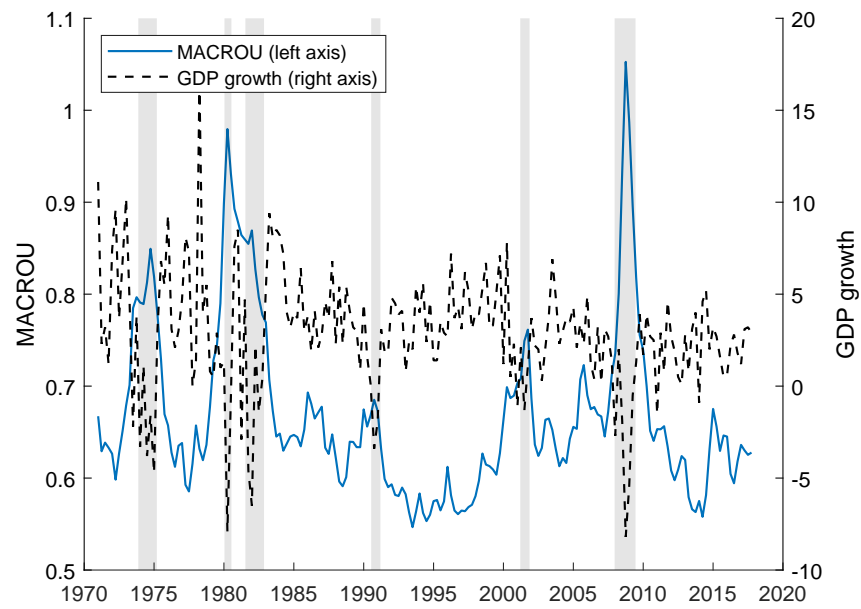
FIGURE 3: MACROU by GDP growth deciles
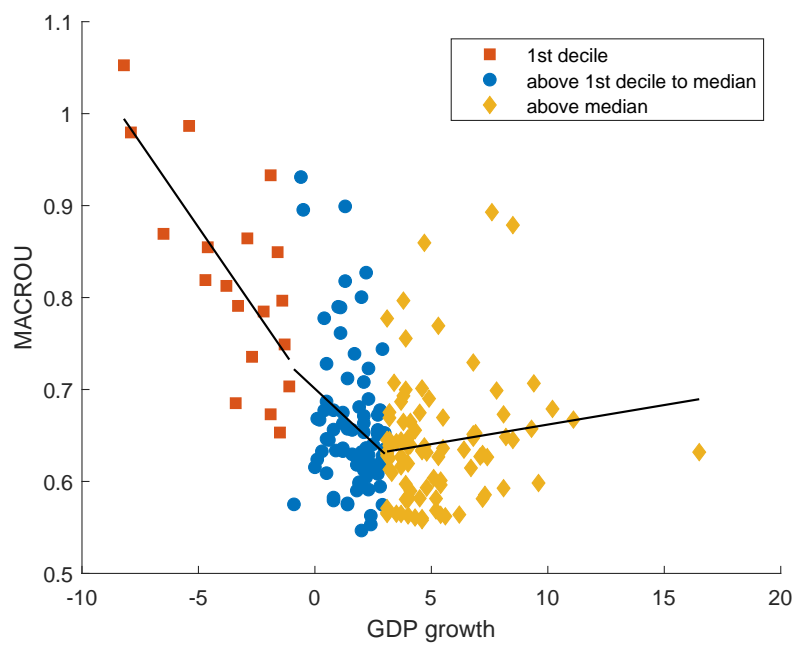

Notes: The sample period covers 1971Q1-2017Q4.

FIGURE 4: Coefficients on MACROU
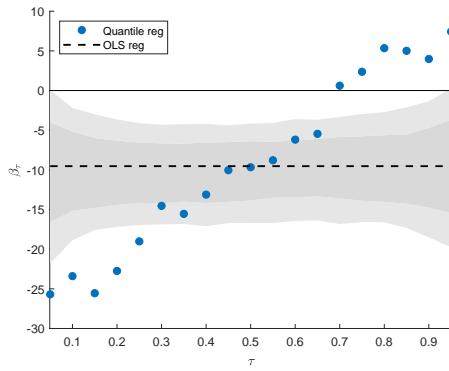
(a) 1Q ahead
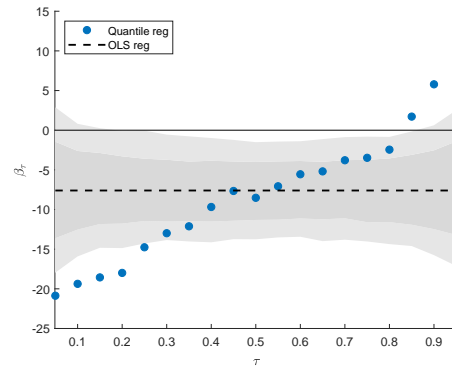
(b) 4Q ahead

Notes: The light/dark gray bands show 90/68 percent confidence bands for a linear model.

FIGURE 5: In-sample predictions for 5th, 50th and 95th quantiles
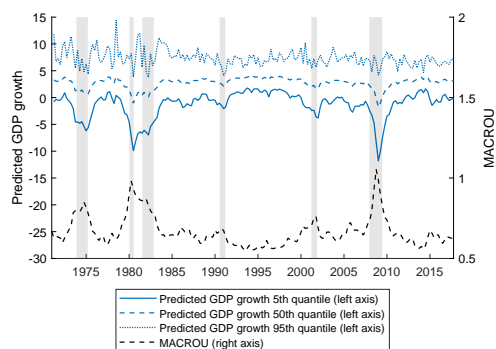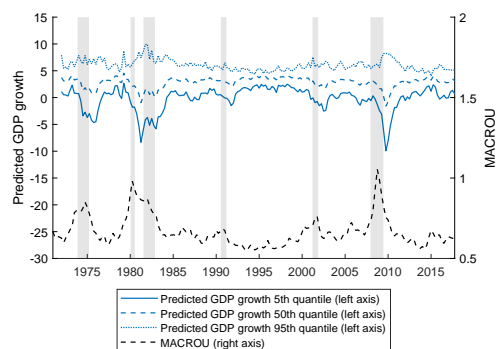
(a) 1Q ahead

(b) 4Q ahead

Notes: The gray bars show NBER-dated recessions.

FIGURE 6: Predictive densities for 2008Q4
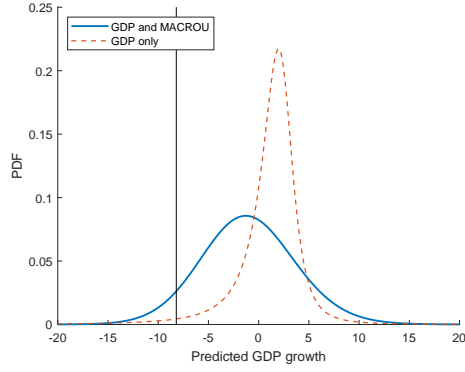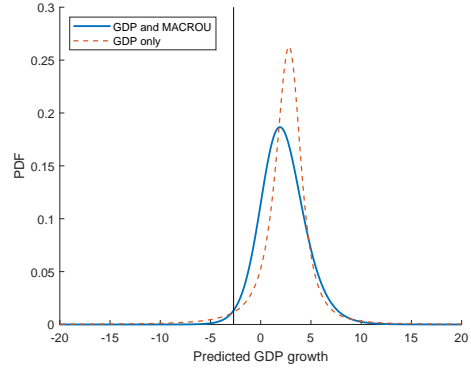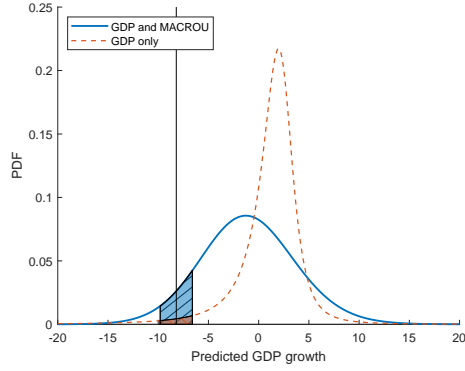
(a) 1Q ahead

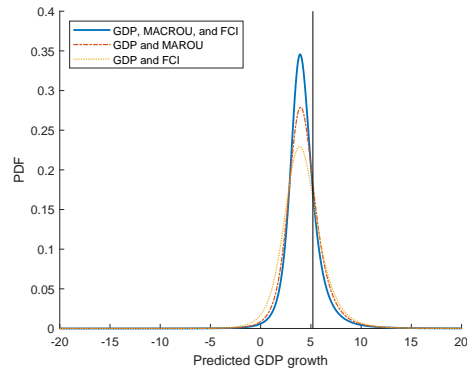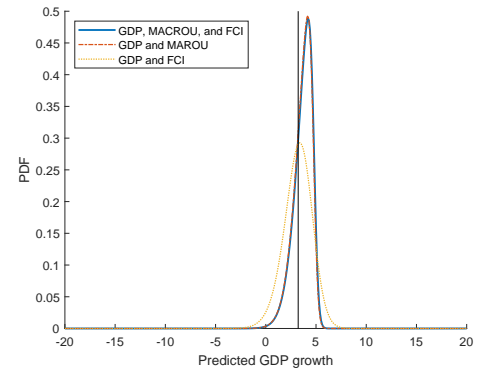(b) 4Q ahead

(c) 1Q ahead
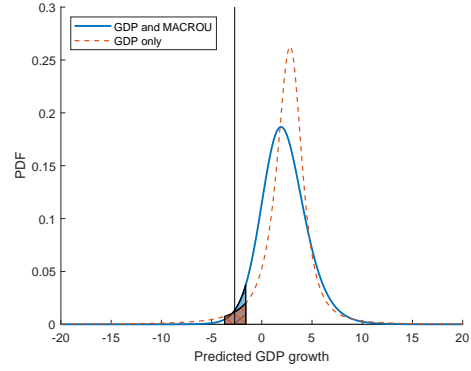
(d) 4Q ahead

Notes: The vertical line depicts the outturn defined as annualized average GDP growth between time t and $t + h$ for the prediction horizon h. The blue shaded area (45 degree hatching pattern) indicates the cumulative probability within one standard deviation of growth around the outturn of the predictive density conditional on current growth and MACROU. The red shaded area (135 degree hatching pattern) indicates the cumulative probability within one standard deviation of growth around the outturn of the predictive density conditional on current growth only.
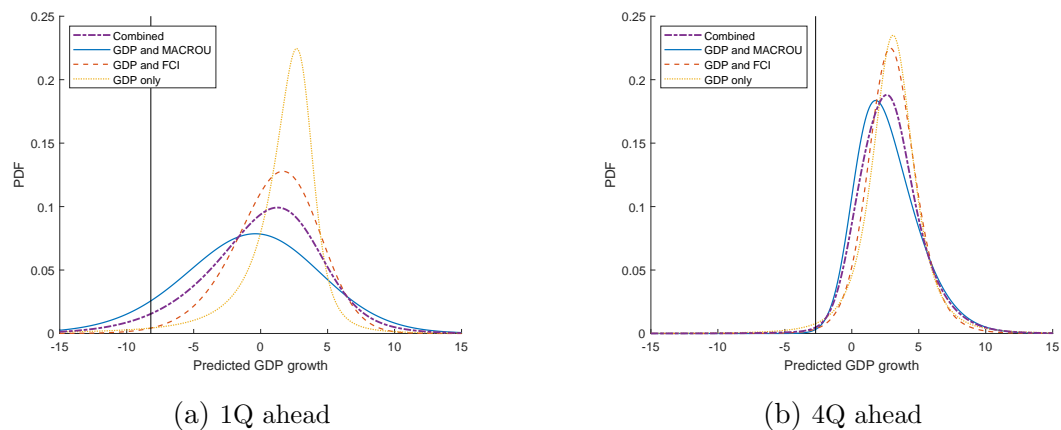
28

FIGURE 7: Predictive densities for 2013Q3
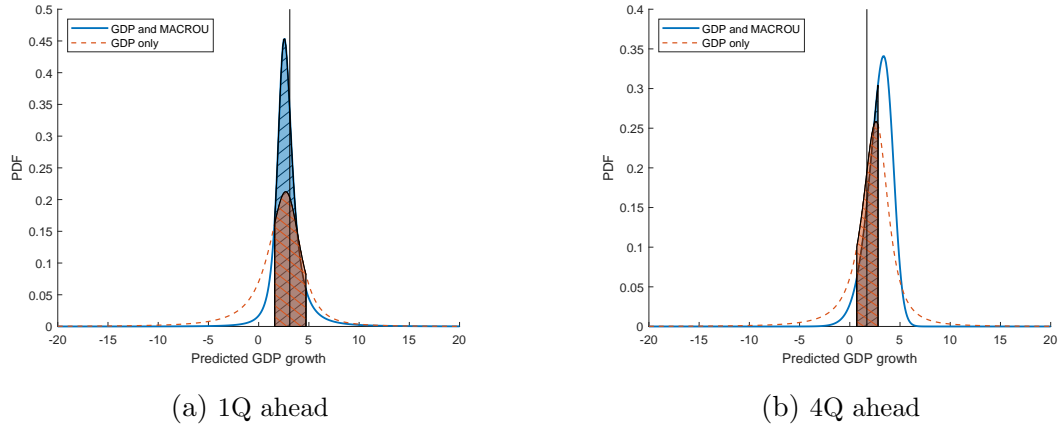
(a) 1Q ahead

(b) 4Q ahead

Notes: The vertical line depicts the outturn defined as annualized average GDP growth between time t and $t + h$ for the prediction horizon h. The blue shaded area (45 degree hatching pattern) indicates the cumulative probability within one standard deviation of growth around the outturn of the predictive density conditional on current growth and MACROU. The red shaded area (135 degree hatching pattern) indicates the cumulative probability within one standard deviation of growth around the outturn of the predictive density conditional on current growth only.

FIGURE 8: Predictive densities for 2014Q3
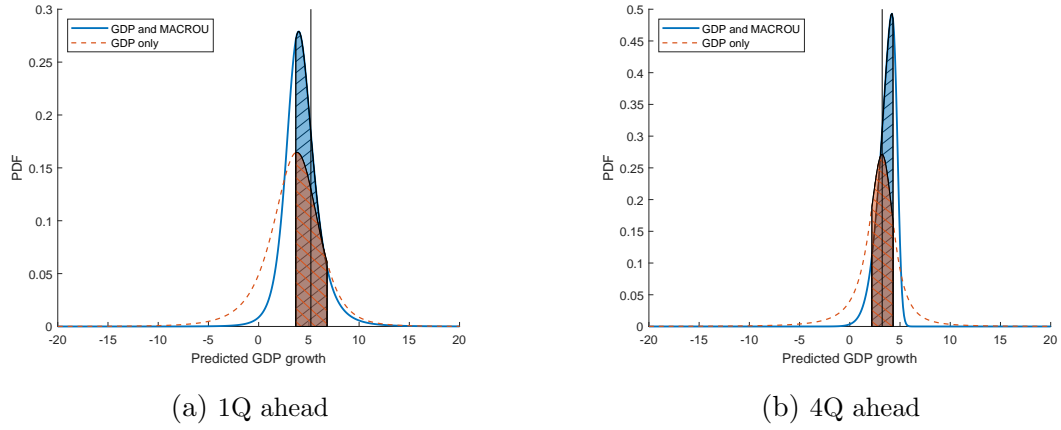
(a) 1Q ahead

(b) 4Q ahead

Notes: The vertical line depicts the outturn defined as annualized average GDP growth between time t and $t + h$ for the prediction horizon h. The blue shaded area (45 degree hatching pattern) indicates the cumulative probability within one standard deviation of growth around the outturn of the predictive density conditional on current growth and MACROU. The red shaded area (135 degree hatching pattern) indicates the cumulative probability within one standard deviation of growth around the outturn of the predictive density conditional on current growth only.

FIGURE 9: In-sample vs out-of-sample predictions for 5th, 50th, and 95th quantiles

(a) 1Q ahead

(b) 4Q ahead
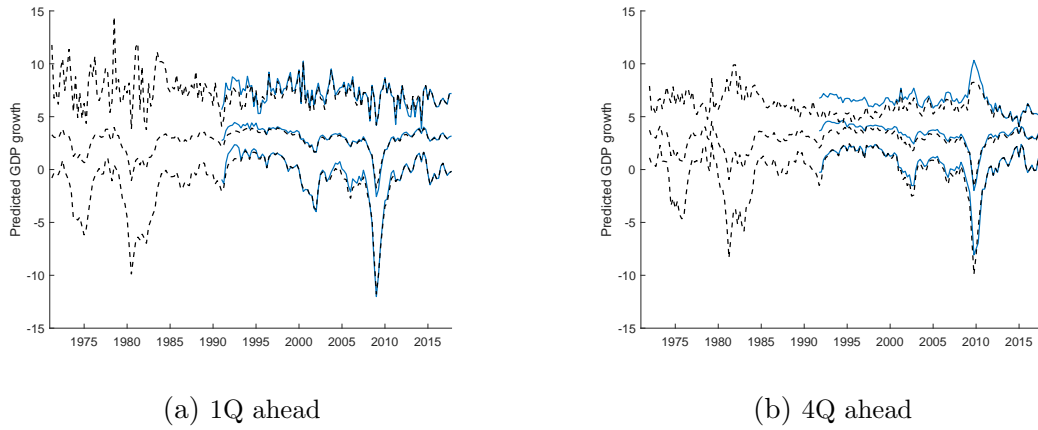
Notes: Predictions conditional on current growth and uncertainty. Out-of-sample predictions based on a recursive window. The initial estimation sample covers 1971Q1–1990Q4 and increases by one quarter during each iteration.

FIGURE 10: Out-of-sample predictive scores
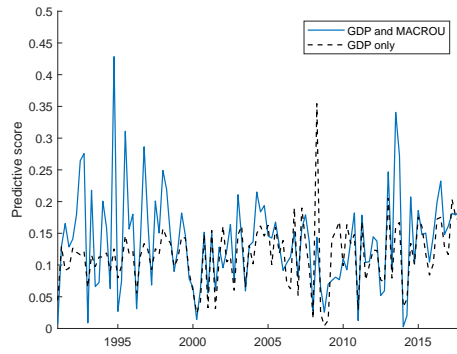
(a) 1Q ahead
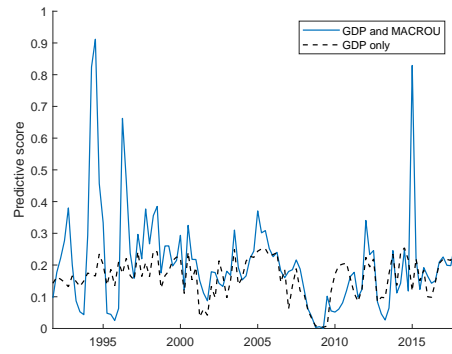
(b) 4Q ahead

Notes: Out-of-sample predictions based on a recursive window. The initial estimation sample covers 1971Q1–1990Q4 and increases by one quarter during each iteration.

FIGURE 11: MACROU and FCI
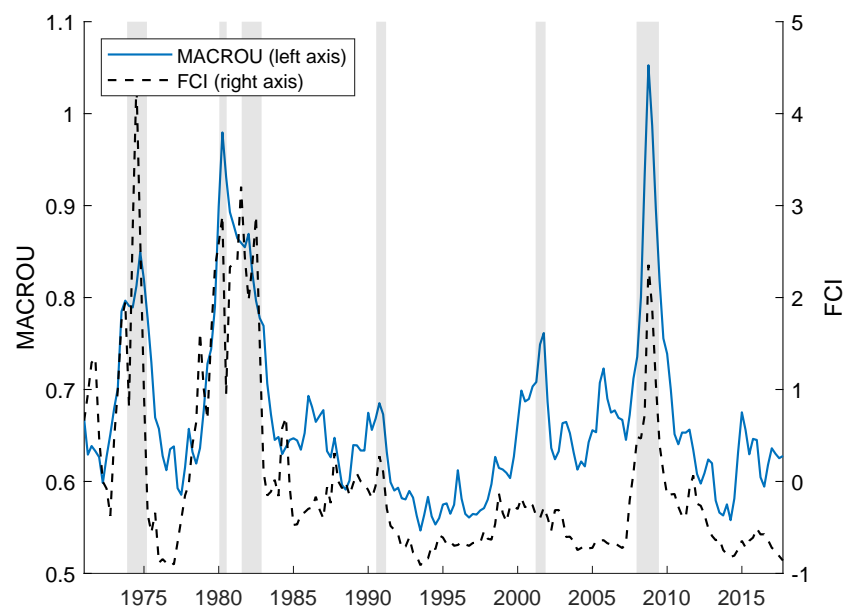
Notes: The gray bars show NBER-dated recessions.

FIGURE 12: Coefficients on MACROU and FCI when conditioning on both
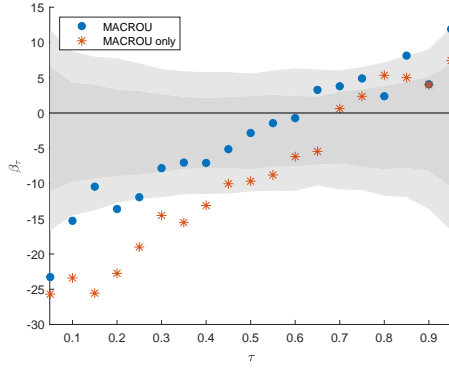
(a) MACROU 1Q ahead
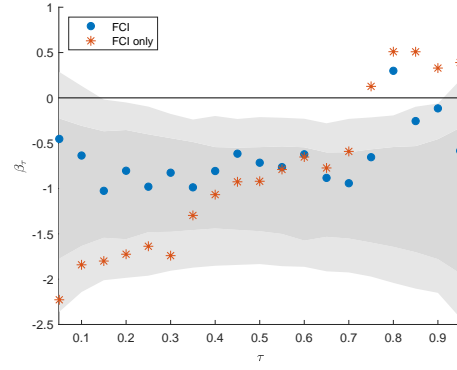
(b) FCI 1Q ahead
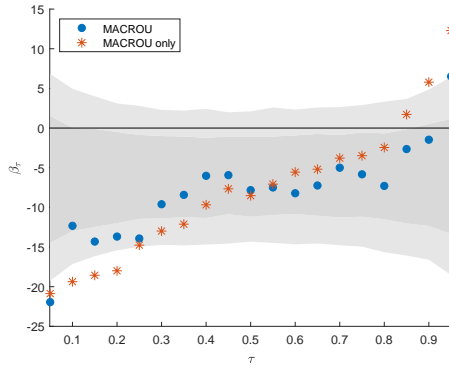
(c) MACROU 4Q ahead
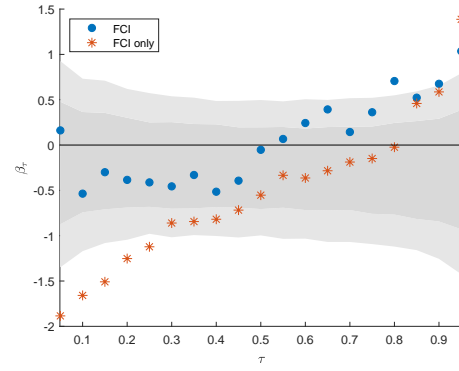
(d) FCI 4Q ahead

Notes: The light/dark gray bands show 90/68 percent confidence bands for a linear model including both MACROU and the FCI.

FIGURE 13: Predictive densities for 2008Q4
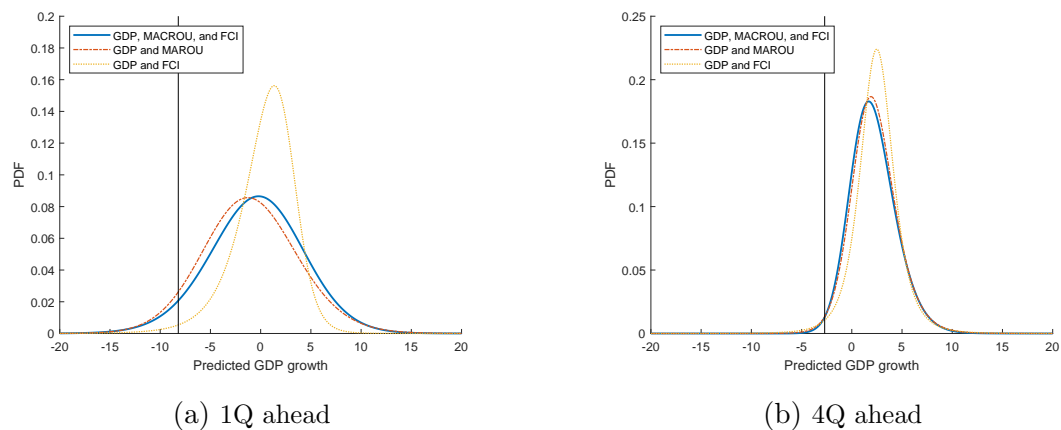
(a) 1Q ahead

(b) 4Q ahead

Notes: The vertical line depicts the outturn defined as annualized average GDP growth between time t and $t + h$ for the prediction horizon h.

FIGURE 14: Predictive densities for 2013Q3
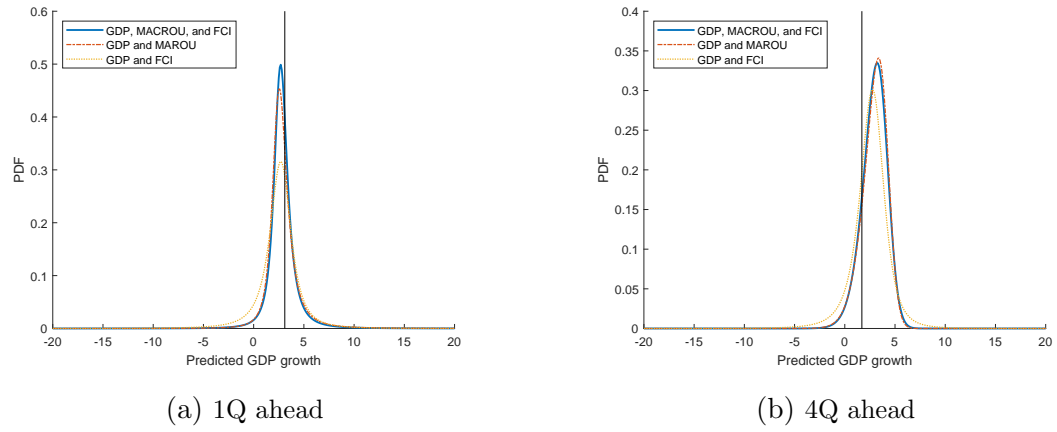
(a) 1Q ahead

(b) 4Q ahead

Notes: The vertical line depicts the outturn defined as annualized average GDP growth between time t and $t + h$ for the prediction horizon h.

FIGURE 15: Predictive densities for 2014Q3

(a) 1Q ahead

(b) 4Q ahead

Notes: The vertical line depicts the outturn GDP growth defined as annualized average GDP growth between time t and $t + h$ for the prediction horizon h.

FIGURE 16: Predictive densities for 2008Q4

(a) 1Q ahead

(b) 4Q ahead

Notes: The vertical line depicts the outturn defined as annualized average GDP growth between time t and $t + h$ for the prediction horizon h. Out-of-sample predictions based on a recursive window. The initial estimation sample covers 1971Q1–1990Q4 and increases by one quarter during each iteration.

FIGURE 17: 5-year rolling window weights
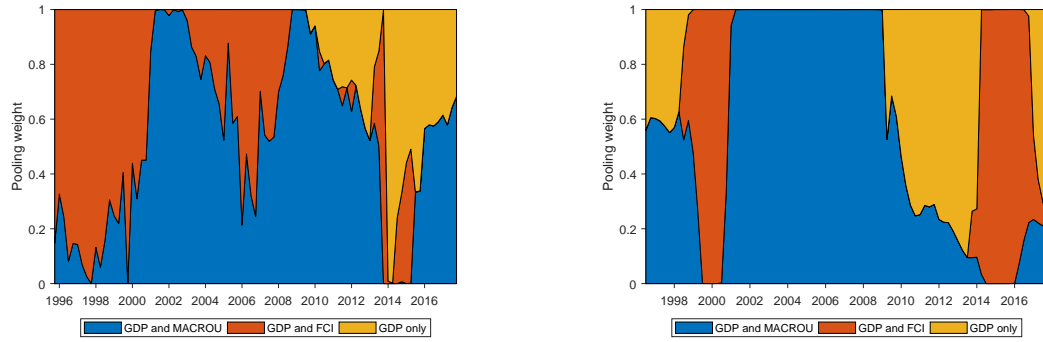
(a) 1Q ahead

(b) 4Q ahead

Notes: The time indicated on the horizontal axis refers to the end of the five-year rolling window.
For example, the first quarter in panel (a), which is 1995Q4, refers to the rolling window from
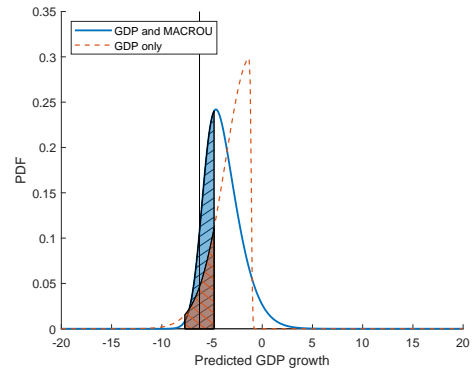1990Q1–1995Q4.
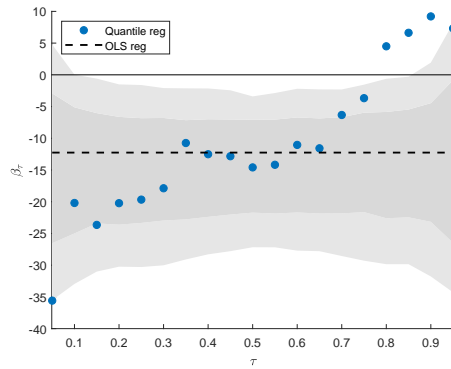
(a) France

(b) Germany

(c) Italy

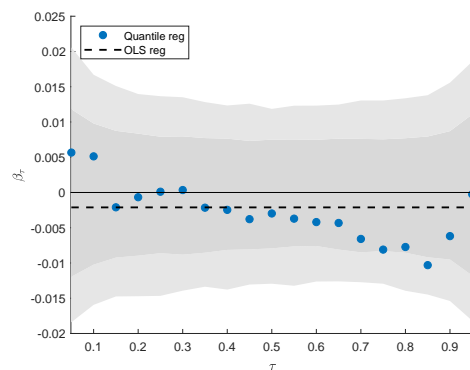(d) Spain

Notes: The sample period covers 1991Q2–2017Q4 for Germany and 1996Q3–2015Q4 for France, Italy, and Spain. The light/dark gray bands show 90/68 percent confidence bands for a linear model.

FIGURE 19: Four-quarter-ahead coefficients on MACROU: France, Germany, Italy, and Spain

(a) France

(b) Germany
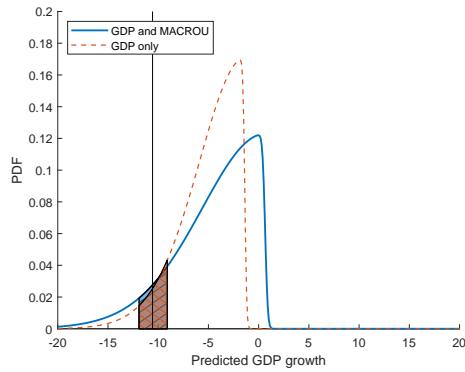
(c) Italy

(d) Spain

Notes: The sample period covers 1991Q2–2017Q4 for Germany and 1996Q3–2015Q4 for France, Italy, and Spain. The light/dark gray bands show 90/68 percent confidence bands for a linear model.

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(a) France

(b) Germany

(c) Italy

(d) Spain

Notes: The sample period covers 1991Q2–2017Q4 for Germany and 1996Q3–2015Q4 for France, Italy, and Spain. The vertical line depicts the outturn defined as annualized average GDP growth between time t and $t + h$ for the prediction horizon h. The blue shaded area (45 degree hatching pattern) indicates the cumulative probability within one standard deviation of growth around the outturn of the predictive density conditional on current growth and MACROU. The red shaded area (135 degree hatching pattern) indicates the cumulative probability within one standard deviation of growth around the outturn of the predictive density conditional on current growth only.

FIGURE 21: Coefficients on EPU
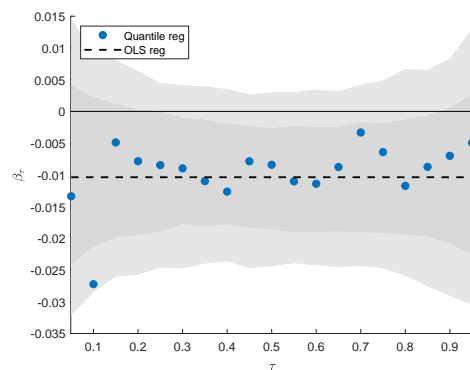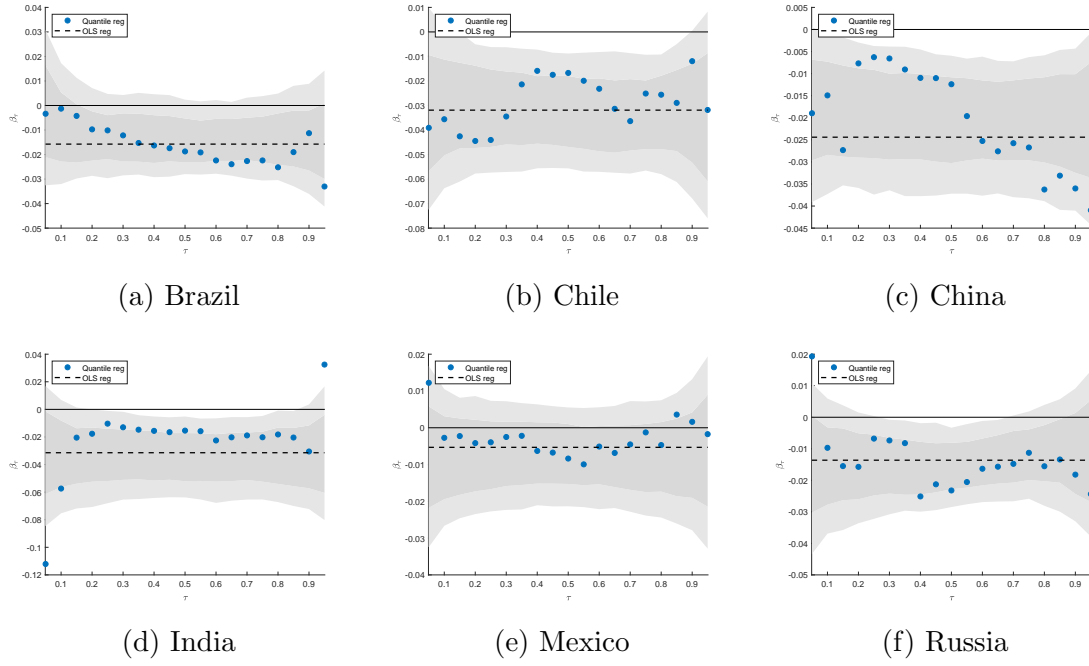

(a) 1Q ahead

(b) 4Q ahead

Notes: The sample period covers 1985Q1–2017Q4. The light/dark gray bands show 90/68 percent confidence bands for a linear model.

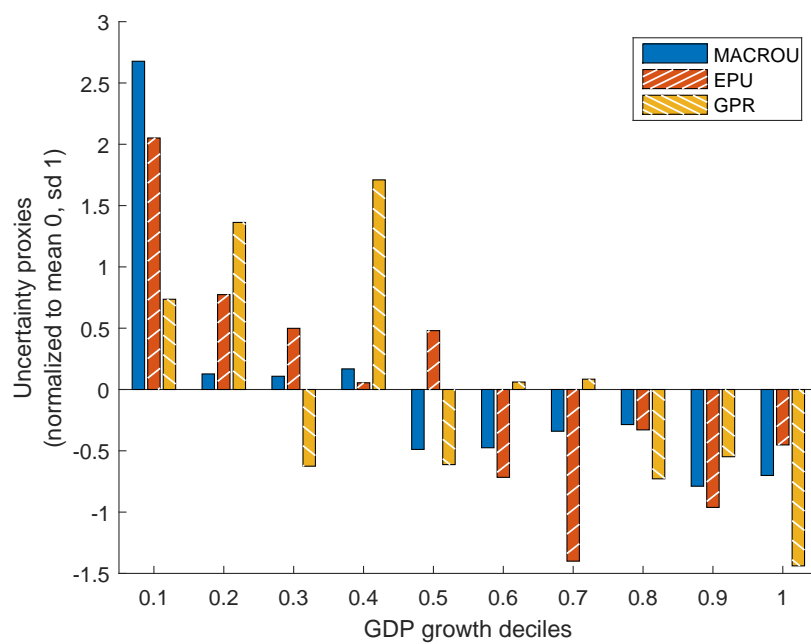FIGURE 22: One-quarter-ahead coefficients on EPU: advanced economies

(a) Australia

(b) Canada

(c) France

(d) Germany

(e) Ireland

(f) Italy

(g) Japan

(h) Korea

(i) Netherlands

(j) Spain

(k) UK

(l) US

Notes: The sample period covers 1985Q1–2017Q4. The sample is unbalanced, however and covers a shorter period for some countries as detailed in Table A.2 in Appendix A. The light/dark gray bands show 90/68 percent confidence bands for a linear model.

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FIGURE 23: One-quarter-ahead coefficients on EPU: emerging market economies

(a) Brazil

(b) Chile

(c) China

(d) India

(e) Mexico

(f) Russia

Notes: The sample period covers 1991Q1–2017Q4. The sample is unbalanced, however and covers a shorter period for some countries as detailed in Table A.2 in Appendix A. The light/dark gray bands show 90/68 percent confidence bands for a linear model.
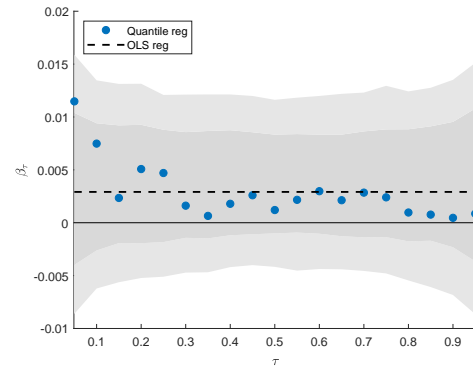
FIGURE 24: Uncertainty by GDP growth deciles

Notes: The sample period covers 1985Q1-2017Q4.

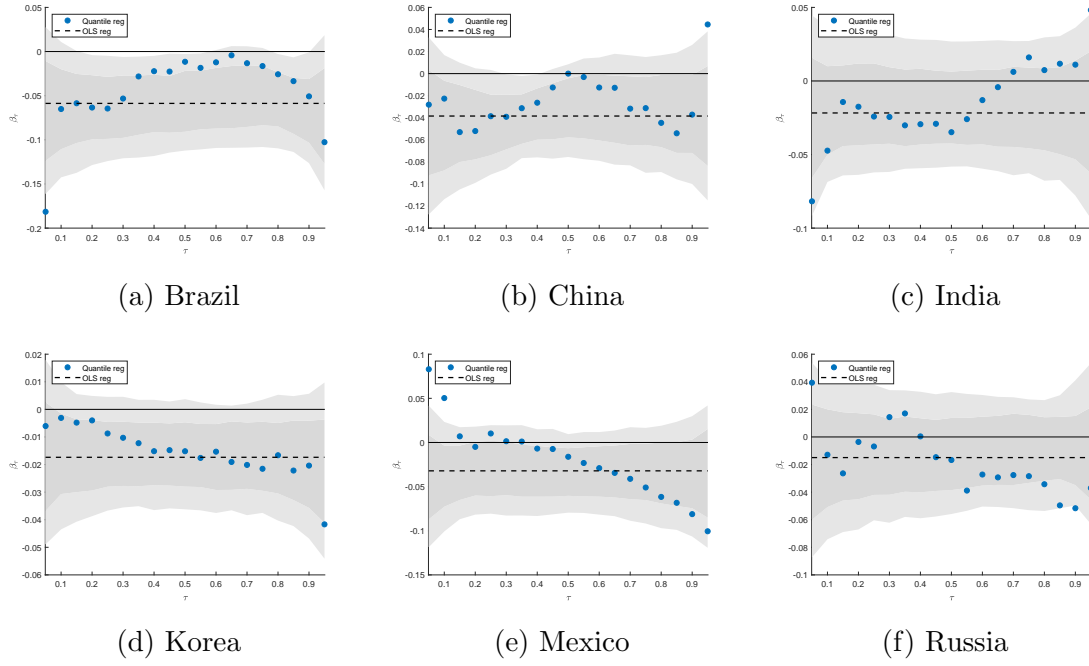FIGURE 25: Coefficients on GPR
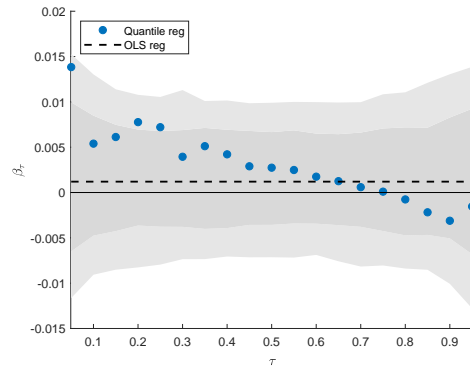
(a) 1Q ahead

(b) 4Q ahead

Notes: The sample period covers 1985Q1–2017Q4. The light/dark gray bands show 90/68 percent confidence bands for a linear model.

FIGURE 26: One-quarter-ahead coefficients on GPR

(a) Brazil

(b) China

(c) India

(d) Korea

(e) Mexico

(f) Russia

Notes: The sample period covers 1985Q1–2017Q4. The light/dark gray bands show 90/68 percent confidence bands for a linear model.

Tables

Table 1: Optimal combination weights

Density	1Q ahead	4Q ahead
Current growth and MACROU	0.5234	0.6578
Current growth and FCI	0.4761	0.0002
Current growth	0.0005	0.3420

Notes: The out-of-sample period covers 1991Q1–2017Q4 for the one-quarter-ahead predictions and 1991Q4–2017Q4 for the four-quarter-ahead predictions.

Appendix A   Dataset

<small>Table</small> A.1: Summary statistics of GDP growth, MACROU, and the FCI

| Variable	Mean	SD	Min	Median	Max
GDP growth	2.63	2.35	-8.20	2.85	7.8
MACROU	0.67	0.09	0.55	0.64	1.05
FCI	0.01	0.99	-0.91	-0.31	4.35

Notes: The sample period covers 1971Q1–2017Q4.

<small>Table</small> A.2: EPU sample period for each country

Country	Sample period
Advanced	
Australia	1998Q1-2017Q4
Canada	1985Q1-2017Q4
France	1987Q1-2017Q4
Germany	1993Q1-2017Q4
Ireland	1985Q1-2017Q4
Italy	1997Q1-2017Q4
Japan	1987Q1-2017Q4
Korea	1990Q1-2017Q4
Netherlands	2003Q2-2017Q4
Spain	2001Q1-2017Q4
UK	1997Q1-2017Q4
US	1985Q1-2017Q4
Emerging	
Brazil	1991Q1-2016Q4
Chile	1995Q2-2017Q4
China	1995Q1-2016Q4
India	2003Q1-2017Q4
Mexico	1996Q1-2017Q4
Russia	2003Q2-2017Q4

Appendix B   Additional Figures

FIGURE B.1: Coefficients on current GDP growth
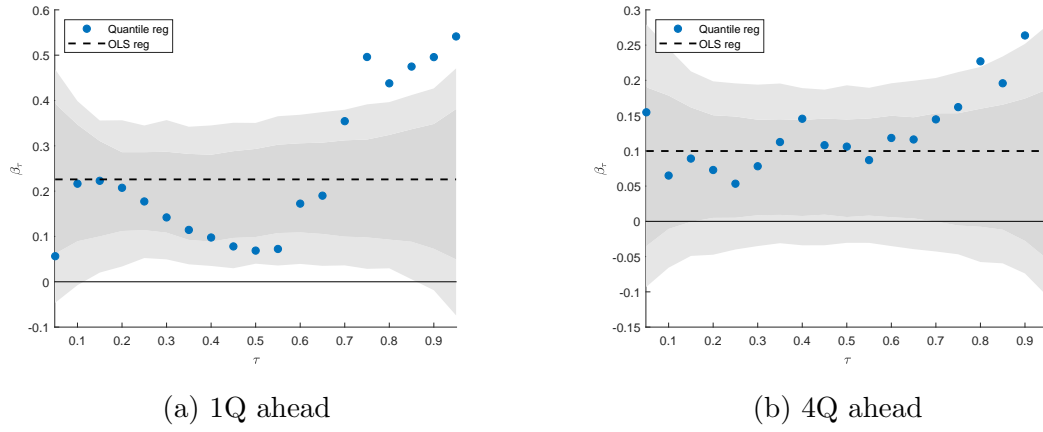
(a) 1Q ahead

(b) 4Q ahead

Notes: The light/dark gray bands show 90/68 percent confidence bands for a linear model.

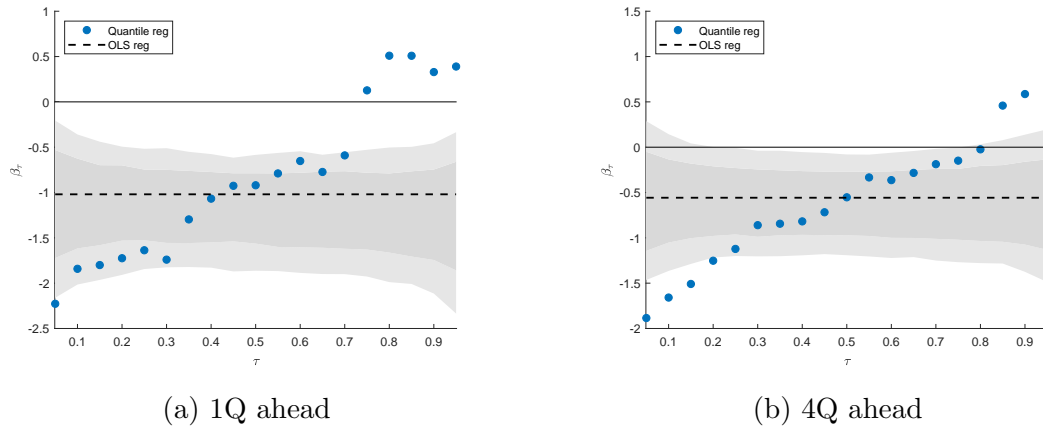FIGURE B.2: Four-quarter-ahead predictive densities
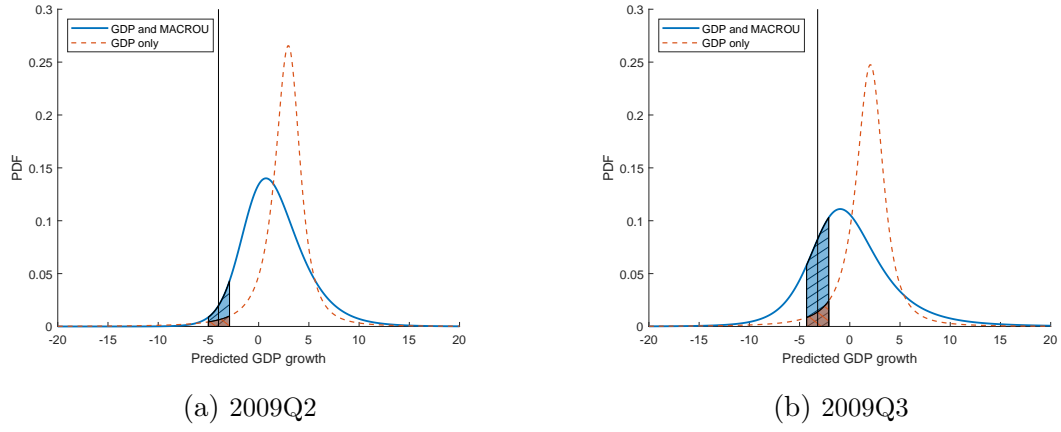
(a) 2009Q2

(b) 2009Q3

Notes: The vertical line depicts the outturn defined as annualized average GDP growth between time t and $t + h$ for the prediction horizon h. The blue shaded area (45 degree hatching pattern) indicates the cumulative probability within one standard deviation of growth around the outturn of the predictive density conditional on current growth and MACROU. The red shaded area (135 degree hatching pattern) indicates the cumulative probability within one standard deviation of growth around the outturn of the predictive density conditional on current growth only.

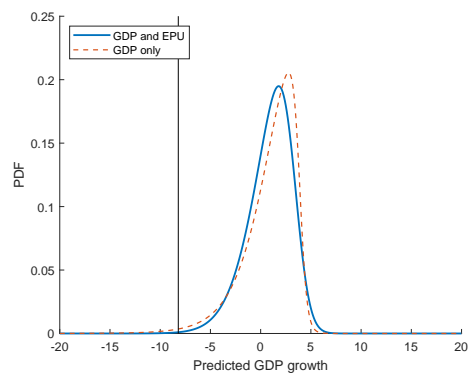FIGURE B.3: Predictive densities for 2008Q4
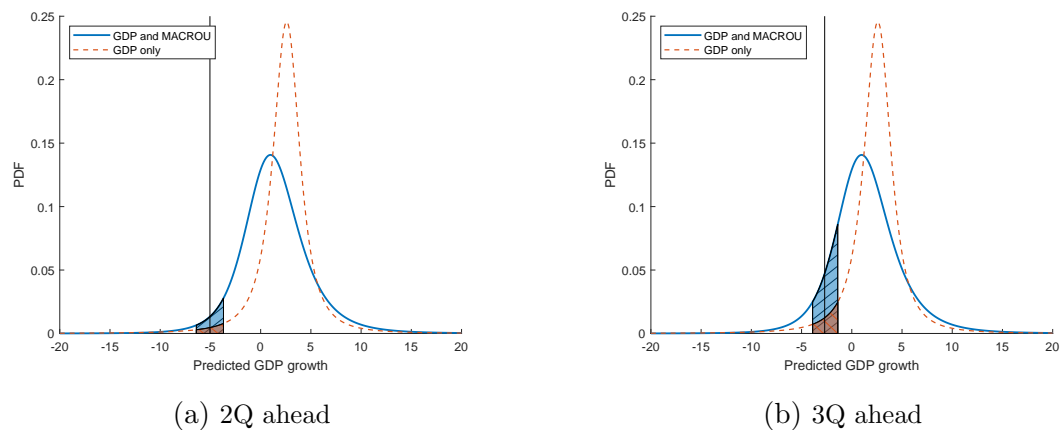
(a) 2Q ahead

(b) 3Q ahead

Notes: The vertical line depicts the outturn defined as annualized average GDP growth between time t and $t + h$ for the prediction horizon h. The blue shaded area (45 degree hatching pattern) indicates the cumulative probability within one standard deviation of growth around the outturn of the predictive density conditional on current growth and MACROU. The red shaded area (135 degree hatching pattern) indicates the cumulative probability within one standard deviation of growth around the outturn of the predictive density conditional on current growth only.

FIGURE B.4: Coefficients on the FCI
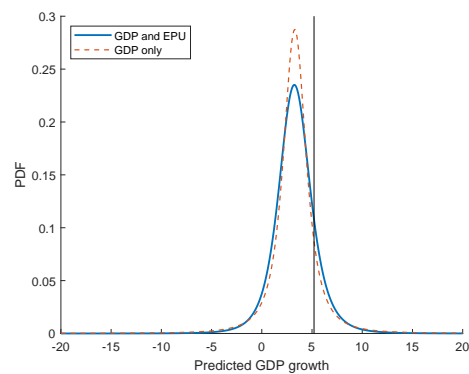

(a) 1Q ahead

(b) 4Q ahead

Notes: The light/dark gray bands show 90/68 percent confidence bands for a linear model.
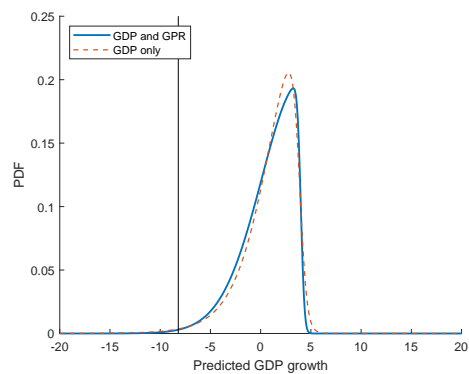
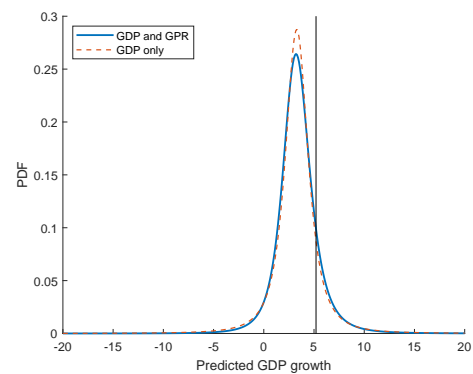FIGURE B.5: One-quarter-ahead predictive densities

(a) 2008Q4

(b) 2014Q3

Notes: The vertical line depicts the outturn defined as annualized average GDP growth between time t and $t+h$ for the prediction horizon h.

FIGURE B.6: One-quarter-ahead predictive densities

(a) 2008Q4

(b) 2014Q3

Notes: The vertical line depicts the outturn defined as annualized average GDP growth between time t and $t + h$ for the prediction horizon h.