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Uncertainty as a Predictor of Economic Activity

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Abstract

Are empirical measures of uncertainty informative about risks to future economic activity? I use quantile regression analysis and density predictions on United States data to show that the relationship between macroeconomic uncertainty and future GDP growth is nonlinear and asymmetric. The left tail of the distribution of future GDP growth is highly responsive to fluctuations in macroeconomic uncertainty, whereas the right tail is relatively stable. As such, macroeconomic uncertainty predicts downside risks to growth but is less informative about upside risks. When combined with an index of financial conditions—a previously proposed predictor of downside risks to growth—macroeconomic uncertainty carries a larger weight in the optimal predictive density. Finally, I provide evidence that alternative empirical measures of uncertainty, such as economic policy uncertainty and geopolitical risk, do not predict risks to the economic outlook. These results hold for a larger sample of countries and underline the importance of differentiating between measures of uncertainty when predicting risks to growth.

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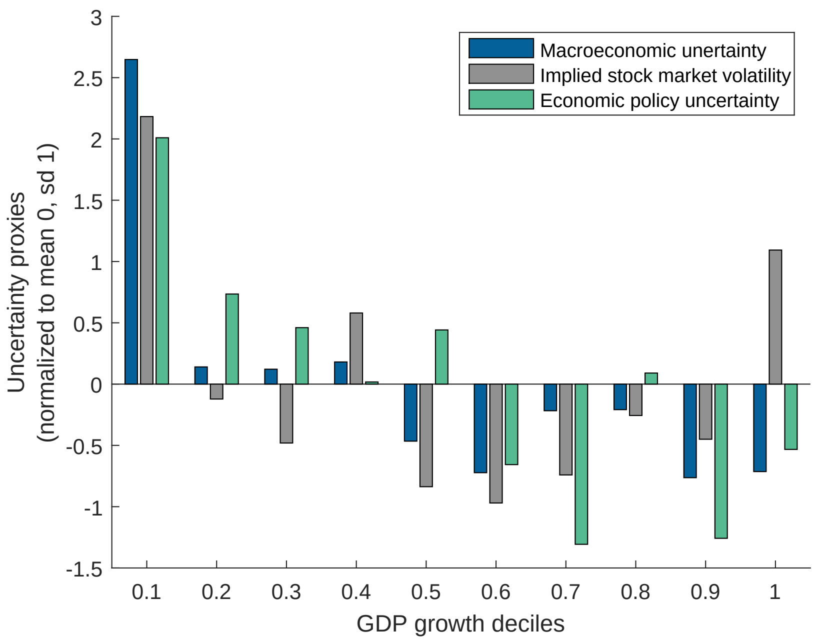
1 Introduction

During the past decade, the United States and many other countries experienced elevated levels of economic and political 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 (see, among others, Bloom, 2014; Bloom et al., 2018; Jurado et al., 2015). 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]

FIGURE 1: Uncertainty by GDP growth deciles



Notes: The sample period covers 1986Q1-2017Q4.

Motivated by this pattern, I investigate whether empirical measures of uncertainty contain information about the distribution of future GDP growth. Predicting the full distribution of future growth—as opposed to a point estimate of the central

[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.

tendency only—can provide insights about risks to growth both on the downside and the upside. It thereby helps to avoid the underestimation of tail risks (Adrian et al., 2018, 2019). Using a novel empirical framework proposed by Adrian et al. (2019), I show that macroeconomic uncertainty predicts downside risks to growth but is less informative about upside risks. My analysis focuses on the US, but I also present evidence for a set of advanced and emerging economies for which suitable data are available.

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 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. (2019).[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 to predict upside risks, although the signal is not as strong as for downside risks. 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 by Adrian et al. (2018, 2019) and IMF (2017) suggests that there is a nonlinear relationship between the financial conditions index and future GDP growth and that financial conditions predict downside risks to growth. The coefficients on macroeconomic uncertainty still vary across the distribution of future growth when I include both

[2] Estimation of the probability density in Adrian et al. (2019) goes back to the work on the skewed t-distribution by Azzalini and Capitanio (2003).

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 a financial conditions index illustrates that both macroeconomic uncertainty and financial conditions predict downside risks to growth but that the magnitude of downside risks associated with macroeconomic uncertainty can be larger.

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 optimally-combined predictive density 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 a 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 during and after the crisis.

In addition, I examine whether two alternative empirical measures of uncertainty yield comparable predictions. I estimate quantile regressions of future growth on economic policy uncertainty, a measure which *prima facie* appears to have similar properties as macroeconomic uncertainty. This exercise provides no compelling evidence of nonlinearities between economic policy uncertainty and future growth, however. Similarly, an index of geopolitical risk does not predict risks to the economic outlook.

Finally, I investigate whether my results generalize to other countries. Quantile regressions of future growth on macroeconomic uncertainty in France, Germany, Italy, and Spain show evidence of nonlinearities, providing further support for macroeconomic uncertainty as a predictor for downside risks to economic activity. In contrast, economic policy uncertainty does not predict risks to growth in a larger set of twelve advanced and emerging market economies and neither does geopolitical risk in a sample of six 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. Studies that rely on point estimates investigate, for example, if uncertainty helps predicting output growth (Caldara et al., 2016; Reif, 2018;

Segnon et al., 2018; Rogers and Xu, 2019), un/employment (Caldara et al., 2016; Reif, 2018; Rogers and Xu, 2019), the equity premium (Gupta et al., 2014), and other indicators of economic activity, such as consumption and investment growth, inflation, and the interest rate (Reif, 2018; Rogers and Xu, 2019).[3]

Only recently have studies begun to incorporate empirical measures of uncertainty in predictions of the distribution of economic activity. For instance, Segnon et al. (2018) use economic policy uncertainty to predict densities of US GNP growth while Reif (2018) analyzes the information content in macroeconomic uncertainty for density predictions for a range of macroeconomic aggregates in the US. Unlike these papers, I focus on the prediction of risks to growth. Moreover, I use a semiparametric approach based on quantile regressions which is straightforward to implement and flexible (see Adrian et al., 2019). In concurrent work, Rogers and Xu (2019) evaluate the predictive power of several uncertainty measures for the quantiles of US GDP growth. While there is some overlap between my work and theirs, I fit and evaluate the entire density of future growth and explore the role of macroeconomic uncertainty and financial conditions when combining predictive densities optimally. In addition, I provide evidence on both the US and a larger set of countries.

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 (see Zarnowitz, 1968). 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. (2019) 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. Moreover, Crump et al. (2018) show that financial conditions also carry predictive information for the distribution of future stock returns. 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

[3] The literature on predicting recessions has also studied uncertainty as a predictor of recession probabilities (see, for example, Balcilar et al., 2016).

GDP 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 and considers alternative measures of uncertainty. In Section 5, I provide evidence for a larger sample of countries. Section 6 concludes and discusses policy implications.

2 Data and Stylized Facts

Uncertainty is a latent variable that cannot be observed directly. A rapidly growing literature has proposed a multitude of proxy measures to quantify the level of uncertainty in the economy. The various available measures rely on vastly different approaches and accordingly capture different sources and types of uncertainty.

Early studies draw on the volatility of financial market outcomes to proxy for uncertainty. For example, Bloom et al. (2007) and Bloom (2009) use the VIX and the volatility of firm-level stock returns to quantify uncertainty, respectively. Similarly, Gilchrist et al. (2014) exploit firm-level stock returns to compute idiosyncratic uncertainty common to all firms in the economy. Other widely used proxies for uncertainty are based on news coverage. This approach was popularized by Baker et al. (2016) who track the frequency of keywords in newspapers to construct an economic policy uncertainty index. Husted et al. (2019) and Caldara and Iacoviello (2018) adopt a similar approach to measure monetary policy uncertainty and geopolitical risk, respectively.

A large number of studies use forecasts to derive measures of uncertainty. For example, Bachmann et al. (2013) propose forecasters' disagreement as a proxy for uncertainty. Jurado et al. (2015) estimate the expected volatility of forecast errors for a large dataset to construct indexes of macroeconomic and financial uncertainty while Jo and Sekkel (2016) define macroeconomic uncertainty as the volatility of a factor common to forecast errors of four different series. Others rely on the distribution of forecast errors of GDP (Rossi and Sekhposyan, 2015) or use forecast errors to construct a high-frequency measure of uncertainty (Scotti, 2016). Yet another approach quantifies uncertainty based on surveys of businesses (see, for example, Altig et al., 2018; Bloom et al., 2019).

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.[4] MACROU is defined as the expected conditional volatility of the unforecastable component of the economy. Based on

[4] Available here.

a stochastic volatility model, uncertainty is estimated for 132 monthly series capturing the macroeconomic environment. The MACROU index is a simple average of the individual uncertainty measures.[5] I took averages across the months within each quarter to transform the monthly index into a quarterly measure.[6]

To study the relative roles of uncertainty and financial conditions, I obtained 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.[7] 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 collected 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 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.[8] Due to limited data availability, the EPU sample is unbalanced. Table A.2 in Appendix A lists the available sample period for each country.

[5] 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.

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

[7] Available here.

[8] 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 indexes across countries, I use the purely news-based index for the US.

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.[9]

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.[10] 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 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 smooth fitted line indicates 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 becomes somewhat weaker. When GDP growth is above the median, the correlation between MACROU

[9] 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.

[10] Available here.

and growth flattens out and then becomes 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. (2019), 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.[11] 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 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

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

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

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 5^{th} and 95^{th} conditional quantiles which are informative about downside and upside risks, respectively. I also show the median (the 50^{th} 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 95^{th} and 50^{th} quantiles are relatively stable over time. The predictions for the 5^{th} conditional quantile, in contrast, vary strongly across time. Increases in MACROU are associated with a widening of the left tail of future growth, 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. (2019), 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: the location (μ), scale (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 5$^{\text{th}}$, 25$^{\text{th}}$, 75$^{\text{th}}$, and 95$^{\text{th}}$ quantiles

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

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 the skewness parameter, θ[12]

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

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 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 sample 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

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

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.[13] 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 (green shaded area).[14] 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).

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 the sample 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.

[13] 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.

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

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 5$^{\text{th}}$, 50$^{\text{th}}$, and 95$^{\text{th}}$ 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 5$^{\text{th}}$ quantile, predicts downside risk to growth even if estimated in pseudo real-time.

To assess the out-of-sample accuracy of the predictions, I analyze the predictive score (PS) and the continuous rank probability score (CRPS). The PS is computed by evaluating the predictive density at the outturn of future GDP growth

$$\mathrm{PS}_{t+h} = \hat{f}_{t+h}(y_{t+h}; \hat{\mu}_{t+h}, \hat{\sigma}_{t+h}, \hat{\nu}_{t+h}, \hat{\theta}_{t+h}). \tag{6}$$

A higher score thus implies that the prediction is more accurate. Figure 10 illustrates that the PS of the density conditional on both current growth and MACROU is higher than the PS 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.

The CRPS generalizes the mean absolute error to probabilistic predictions. It takes into account both the location and scale of the predictive cumulative distribution function in assessing the accuracy of the prediction. Unlike the PS, it thereby also assesses predictions that are near the outturn but not identical. The CRPS between the outturn y and the predictive distribution function $\hat{F}$ is defined as

$$\mathrm{CRPS}_{t+h} = \int_{-\infty}^{\infty} \left(\hat{F}_{t+h} - \mathbb{1}(y_{t+h} \leq \hat{y}_{t+h})\right)^2 \mathrm{d}\hat{y}_{t+h} \tag{7}$$

where $\mathbb{1}$ is an indicator function (see Gneiting and Ranjan, 2011). The CRPS is expressed in units of the observed variable (percent), whereby a lower score indicates higher accuracy. Figure 11 shows the CRPSs for the density conditioning on current growth only and the density conditioning on current growth and MACROU. The latter is smaller than the former 65 percent and 63 percent of the out-of-sample period one quarter ahead (panel (a)) and four quarters ahead (panel (b)), respectively. These results are robust to using a recursively-estimated MACROU index and real-time GDP data.[15]

4 Alternative Predictors of Risks to Growth

This section investigates the role of financial conditions which have been proposed previously as a predictor of downside risks to growth. I illustrate how MACROU and the financial conditions index (FCI) compare in predicting growth and how they can be combined optimally. I also contrast the properties of economic policy uncertainty (EPU) and geopolitical risk (GPR)—two widely used proxies for uncertainty—to those of MACROU and investigate whether these alternative measures of uncertainty predict risks to growth.

4.1 Financial Conditions

Adrian et al. (2018, 2019) and IMF (2017) highlight that a tightening of financial conditions predicts downside risks to growth. Figure 12 shows that the FCI and MACROU strongly comove with a correlation coefficient of 0.8 over the sample period from 1971Q1–2017Q4. 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 13 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

[15] These results are available upon request.

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 (d)). As above, the confidence bands are somewhat wider, reflecting the collinearity between MACROU and the FCI (see Figure B.3 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 14 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 15), and during economic upswings, such as in 2014Q3 (Figure 16), neither MACROU nor the FCI predict 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.

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).[16] Let $\hat{f}_{t+h}(\cdot)$ denote the

[16]For other papers that study similar methods to combine density forecasts see, for example,

optimally-combined density which is a weighted average of N individual predictive density

$$\hat{f}_{t+h}(\cdot) = \sum_{i=1}^{N} \omega_i \hat{f}_{i,t+h|t}(\cdot), \qquad i = 1, ..., N \tag{8}$$

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 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 PS

$$\phi(\boldsymbol{\omega}) = \frac{1}{T-h} \sum_{t=1}^{T-h} \ln \hat{f}_{t+h}(y_{t+h}). \tag{9}$$

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

$$\omega_i^{(k+1)} = \omega_i^{(k)} \frac{1}{T-h} \sum_{t=1}^{T-h} \frac{\hat{f}_{i,t+h}(y_{t+h})}{\sum_{l=1}^{N} \hat{f}_{l,t+h}(y_{t+h}) \omega_l^{(k)}}. \tag{10}$$

I simultaneously estimate the optimal weights associated with each predictive density by running the algorithm in equation (10) 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

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.

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 17 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 18 shows the optimal weights for one-quarter-ahead predictions. The weights for each predictive density vary strongly across time, or perhaps 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. During and after 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 real time 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.

4.2 Alternative Proxies for Uncertainty

Alternative proxies for uncertainty that have been used in empirical applications are, for example, EPU and GPR. At first glance, EPU appears to have similar properties to MACROU. Figure 19 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. This is not the case for the GPR index. Nonetheless, GPR tends to be higher, on average, when growth is below the median.

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 20 presents the results. Both one and four quarters ahead, the relationship between future growth and EPU does not exhibit significant nonlinearities. In contrast to what Figure 19 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.4 in Appendix B).[17,18] This result is similar to Rogers and Xu (2019) who do not find a significant relationship between EPU and the quantiles of the GDP growth distribution, except for the 10$^{\text{th}}$ quantile at the one-quarter-ahead horizon.[19]

In addition, I examine whether GPR predicts risks to growth. I again proceed by re-estimating equation (1) conditional on a constant, current GDP growth, and GPR. Figure 21 presents the coefficients on the GPR index. 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 (see Figure B.5 in Appendix B).

[17] 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).

[18] 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.

[19] Rogers and Xu (2019) evaluate the statistical significance with respect to zero whereas my paper explores the significance of nonlinearities.

5 International Evidence

This section explores whether MACROU predicts risks to growth in France, Germany, Italy, and Spain. I also investigate if EPU and GPR are informative about risks to growth in a larger sample of advanced and emerging market economies.

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.[20] 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 22 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 23 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 24 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 (green 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.

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.[21] Figure 25 displays the coefficients on EPU

[20] Table C.3 in Appendix C presents the correlation between the MACROU indexes in Europe.

[21] 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,

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 26, 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.

Finally, I examine whether GPR predicts risks to growth for a sample of six other economies.[22] The relationship between GPR and future GDP growth is relatively stable across the distribution of future growth in those economies in my sample (Figure 27). 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 empirical measures of uncertainty are informative about risks to future GDP growth. My findings suggest that periods of high macroeconomic 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

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.

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

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 necessarily 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. They confirm that predicting the full density of growth is more informative than a simple point prediction. Predictive densities enable policymakers to detect risks to growth, particularly on the downside. 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 as has also been pointed out by Adrian et al. (2018). Scenario analysis is an increasingly relevant policy tool in a world in which tail risks remain large. 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 considerably 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.

My findings open several avenues for future research. First, an important task 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, 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

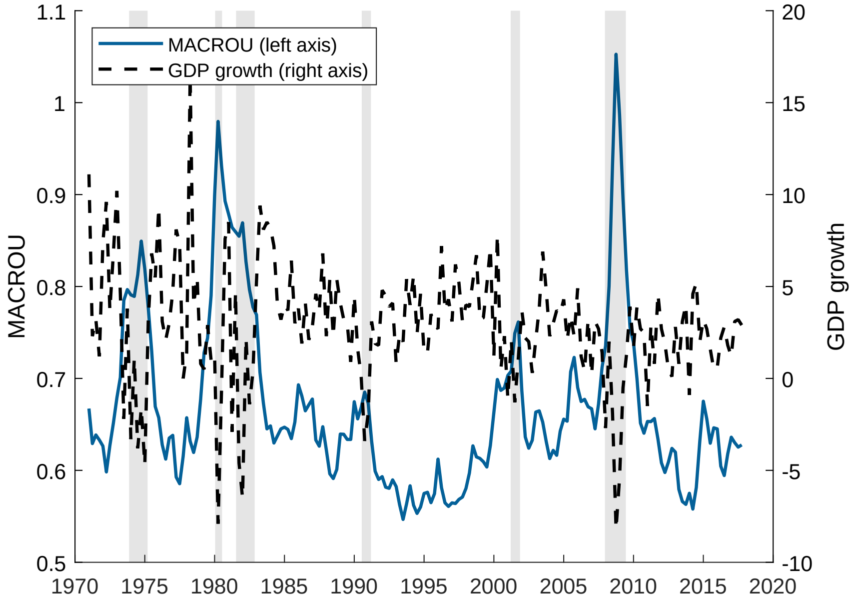
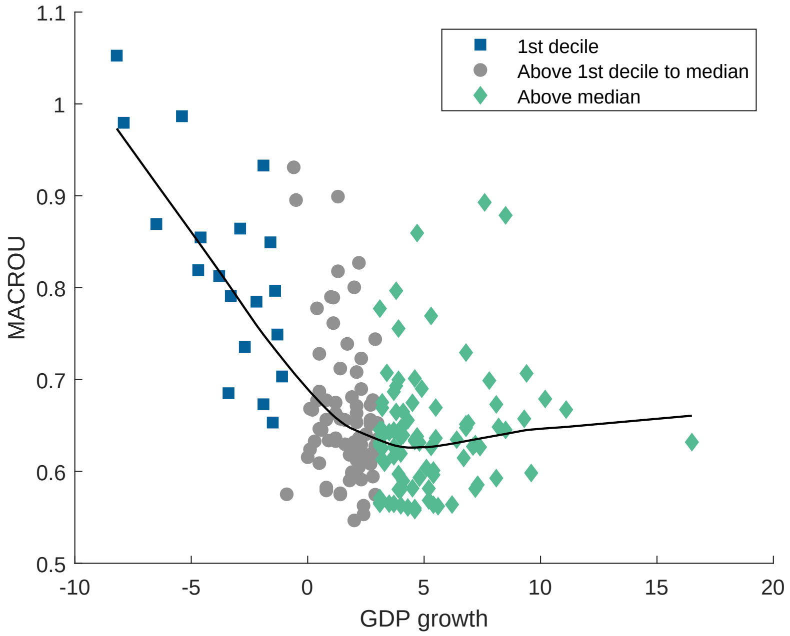
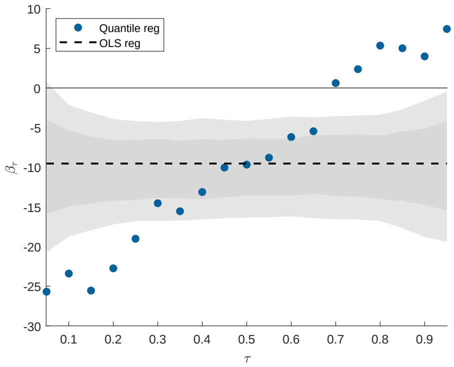


Figure 3: MACROU by GDP growth deciles

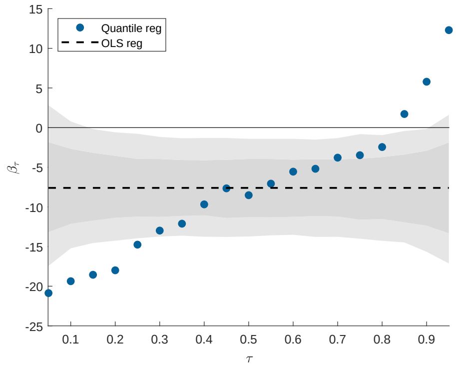


Notes: The sample period covers 1971Q1-2017Q4.

Figure 4: Coefficients on MACROU



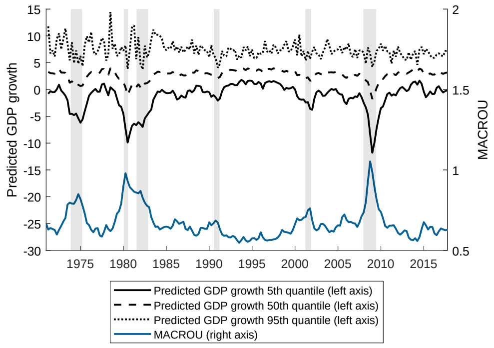
(a) 1Q ahead



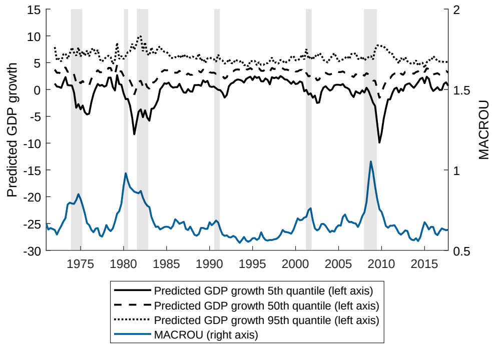
(b) 4Q ahead

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

Figure 5: In-sample predictions for 5^{th}, 50^{th} and 95^{th} quantiles



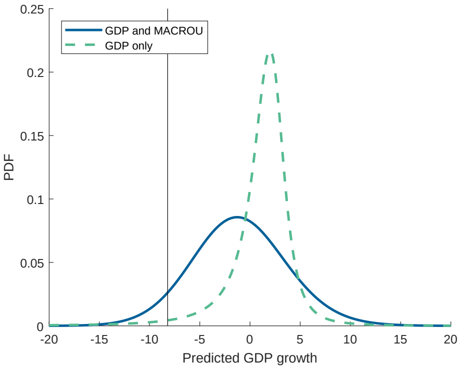
(a) 1Q ahead



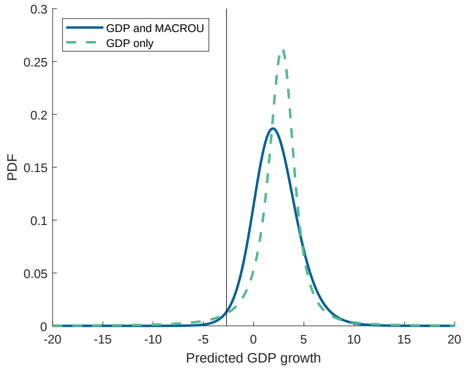
(b) 4Q ahead

Notes: The gray bars show NBER-dated recessions.

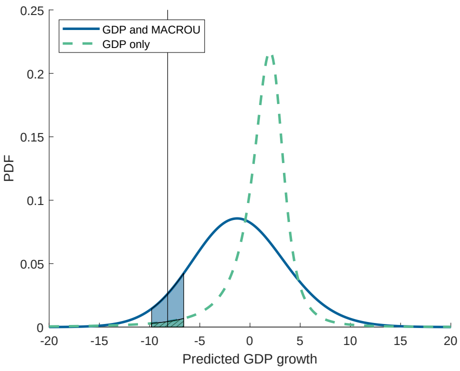
Figure 6: Predictive densities for 2008Q4



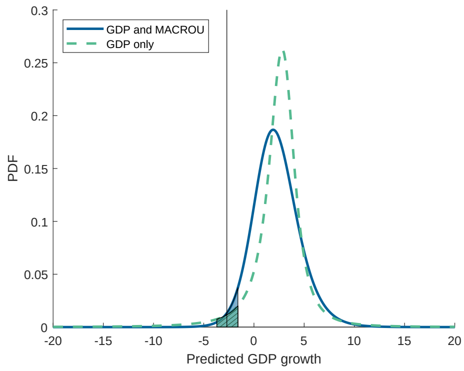
(a) 1Q ahead



(b) 4Q ahead



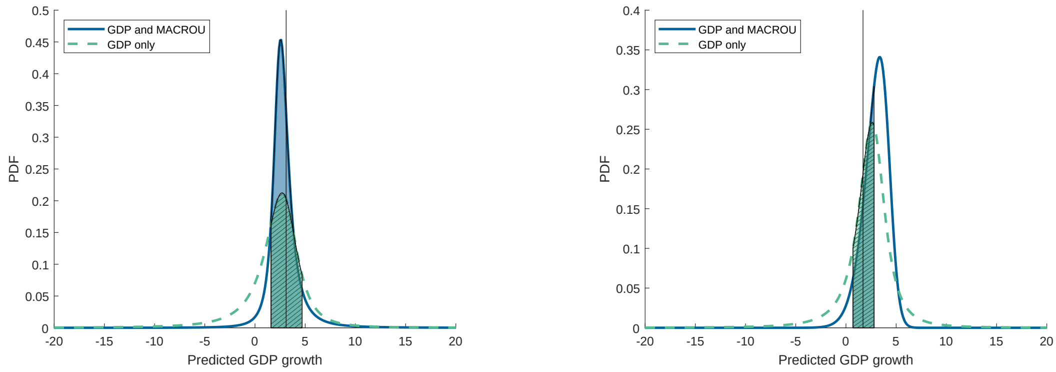
(c) 1Q ahead



(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 indicates the cumulative probability within one standard deviation of growth around the outturn of the predictive density conditional on current growth and MACROU. The green shaded area (hatching pattern) indicates the cumulative probability within one standard deviation of growth around the outturn of the predictive density conditional on current growth only.

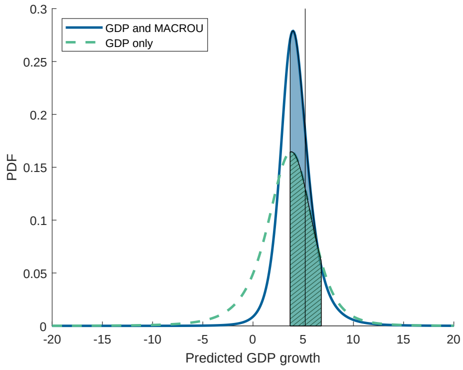
Figure 7: Predictive densities for 2013Q3



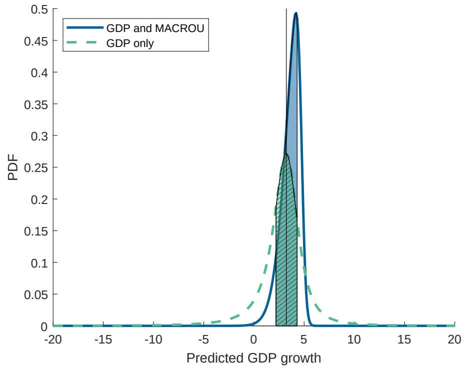
(a) 1Q ahead (b) 4Q ahead

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 indicates the cumulative probability within one standard deviation of growth around the outturn of the predictive density conditional on current growth and MACROU. The green shaded area (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



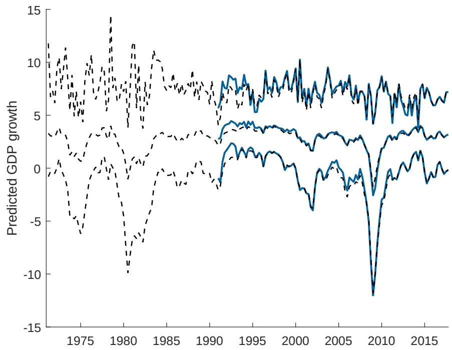
(a) 1Q ahead



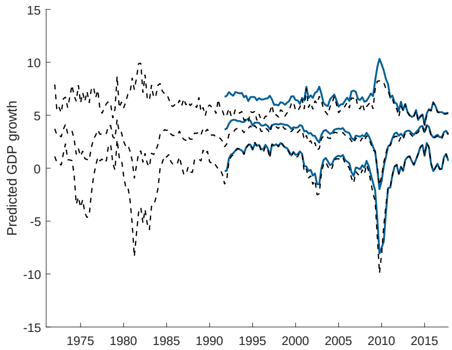
(b) 4Q ahead

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 indicates the cumulative probability within one standard deviation of growth around the outturn of the predictive density conditional on current growth and MACROU. The green shaded area (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 5^{th}, 50^{th}, and 95^{th} quantiles



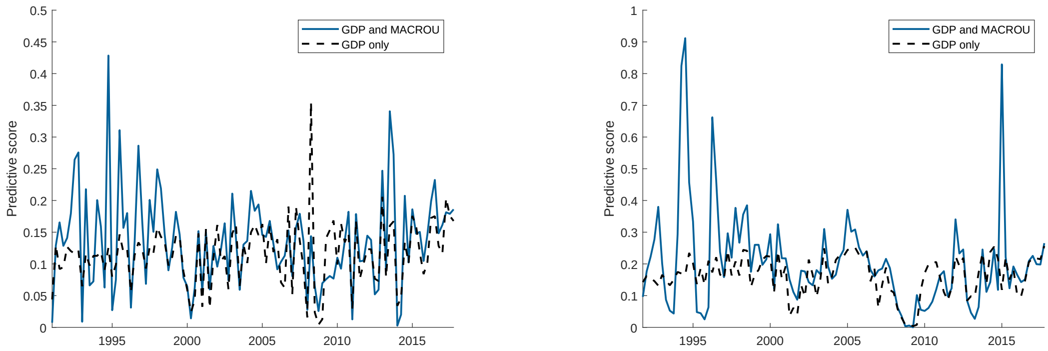
(a) 1Q ahead



(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

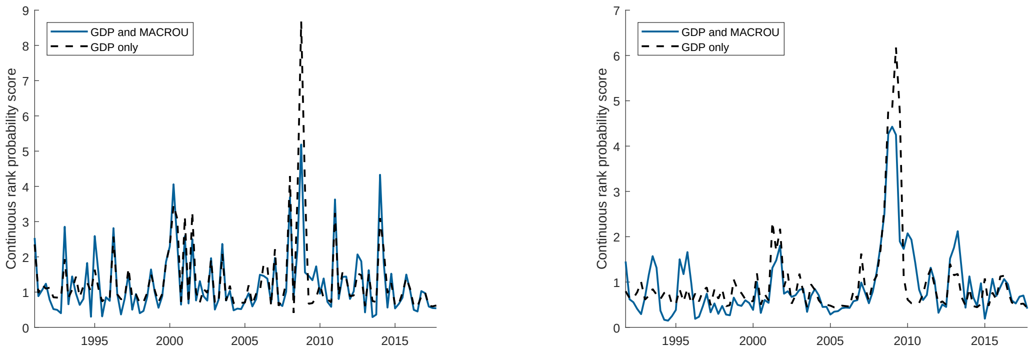


(a) 1Q ahead

(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: Out-of-sample continuous rank probability score

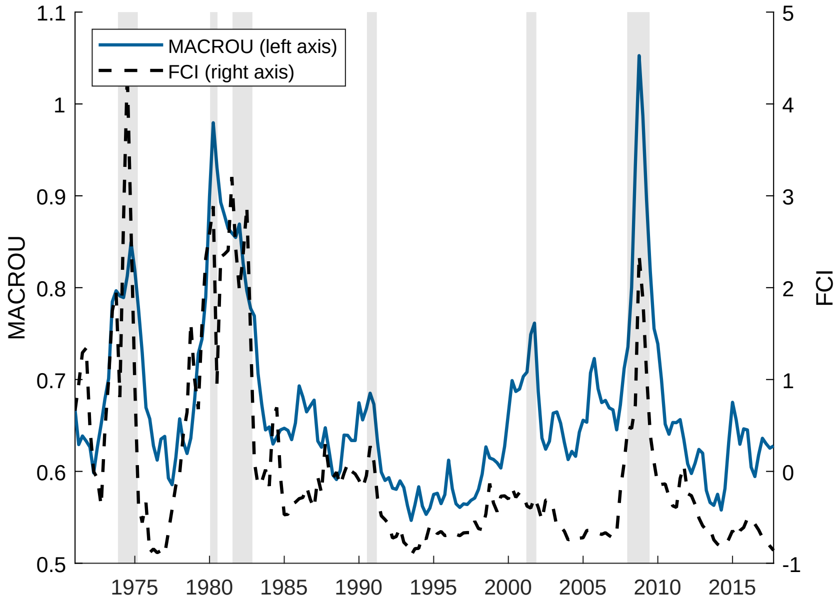


(a) 1Q ahead

(b) 4Q ahead

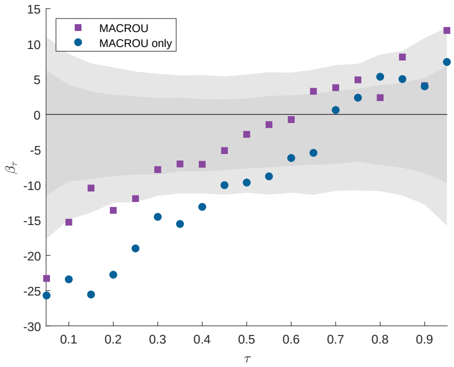
Notes: Out-of-sample predictions based on a recursive window. The initial estimation sample covers 1971Q1–1990Q4 and increases by one quarter during each iteration.

Figure 12: MACROU and FCI

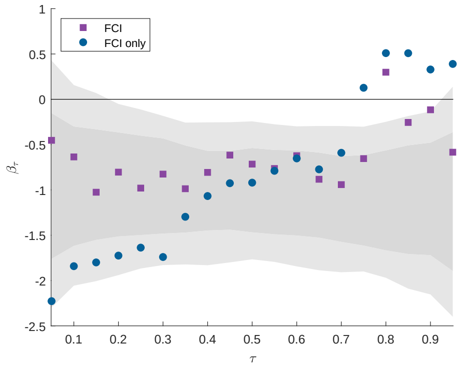


Notes: The gray bars show NBER-dated recessions.

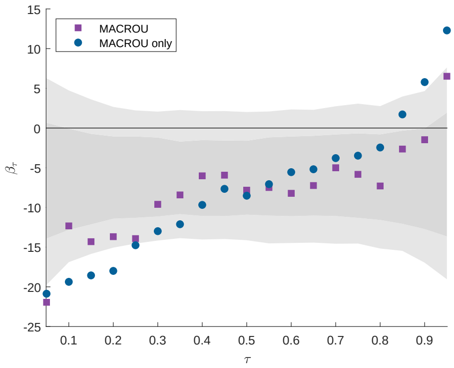
Figure 13: Coefficients on MACROU and FCI when conditioning on both



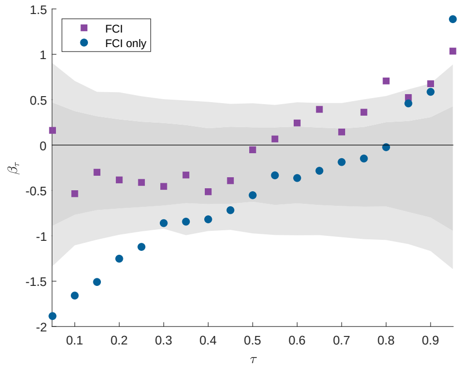
(a) MACROU 1Q ahead



(b) FCI 1Q ahead



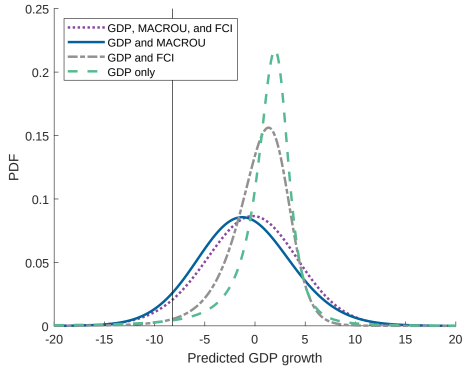
(c) MACROU 4Q ahead



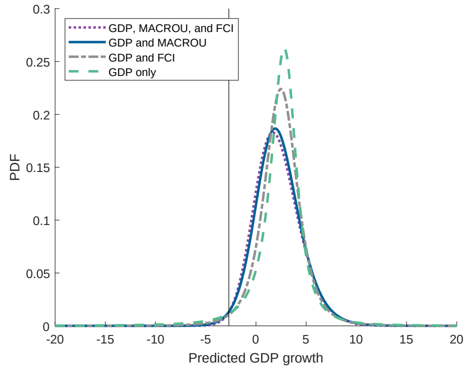
(d) FCI 4Q ahead

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

Figure 14: Predictive densities for 2008Q4



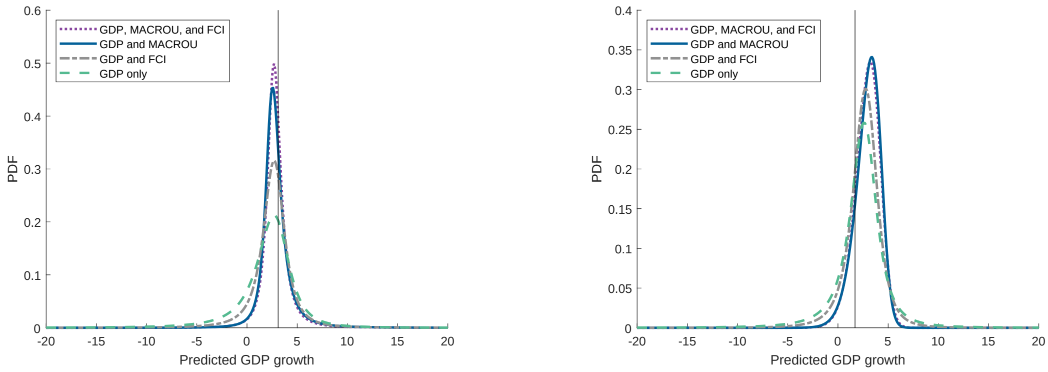
(a) 1Q ahead



(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 15: Predictive densities for 2013Q3

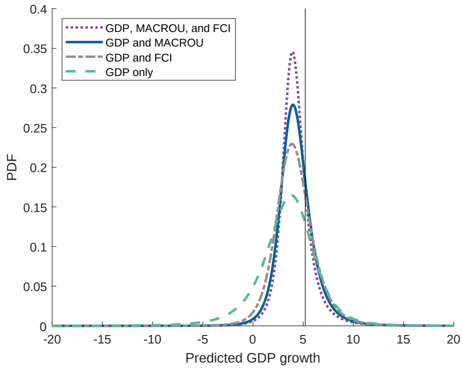


(a) 1Q ahead

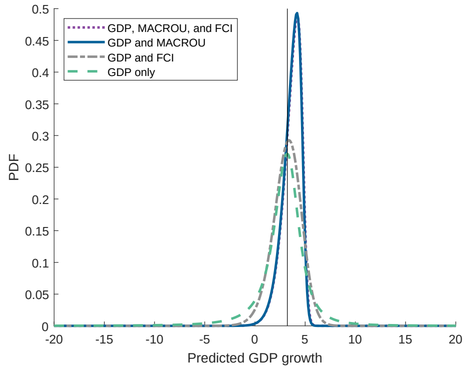
(b) 4Q ahead

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 16: Predictive densities for 2014Q3



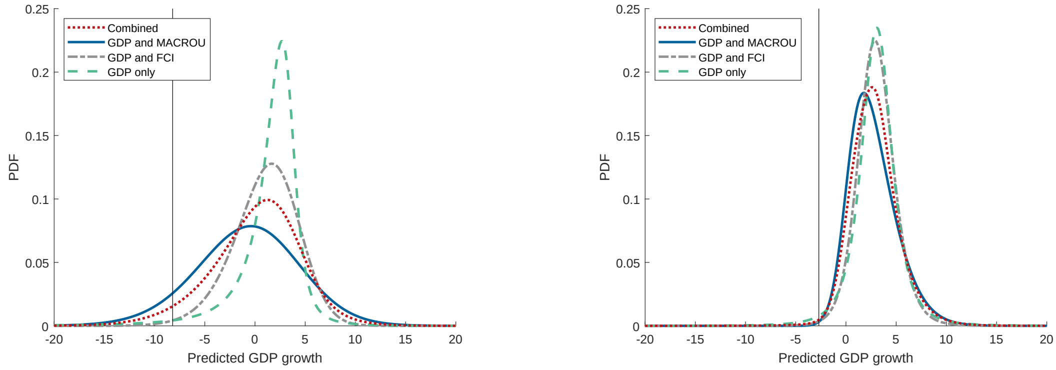
(a) 1Q ahead



(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 17: Predictive densities for 2008Q4

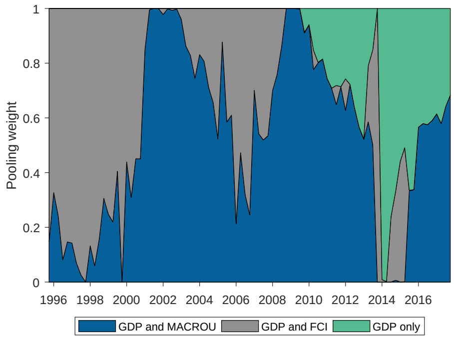


(a) 1Q ahead

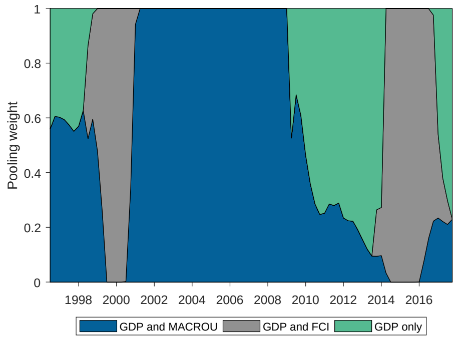
(b) 4Q ahead

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 18: 5-year rolling window weights



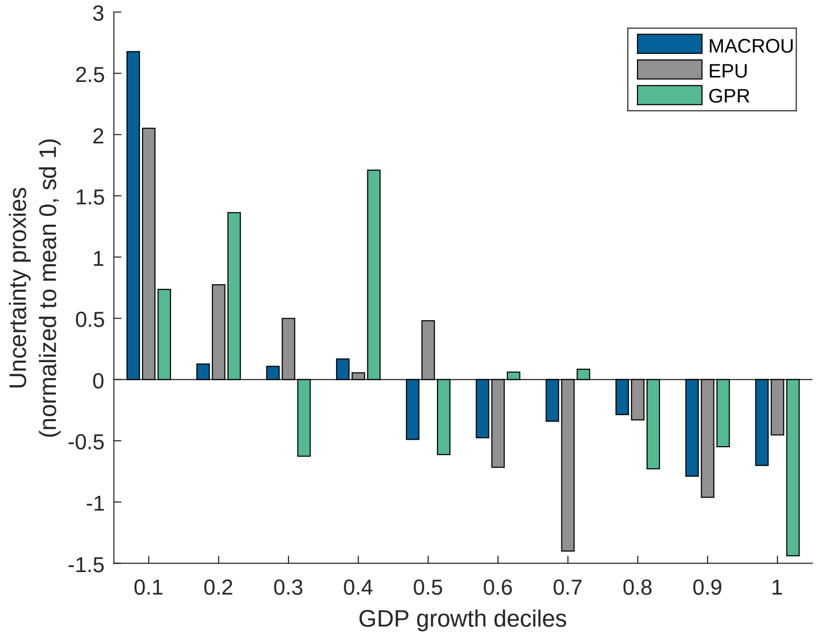
(a) 1Q ahead



(b) 4Q ahead

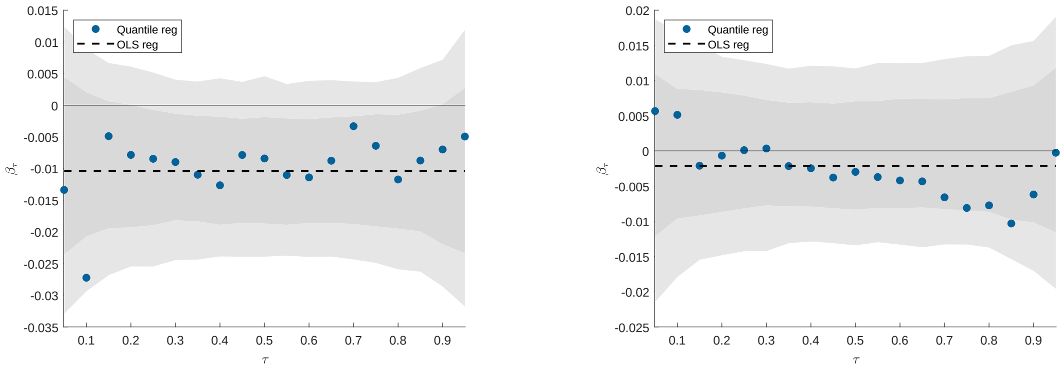
Notes: The time indicated on the horizontal axis refers to the end of the five-year rolling window. For example, the first quarter in panel (a), which is 1995Q4, refers to the rolling window from 1990Q1–1995Q4.

Figure 19: Uncertainty by GDP growth deciles



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

Figure 20: Coefficients on EPU

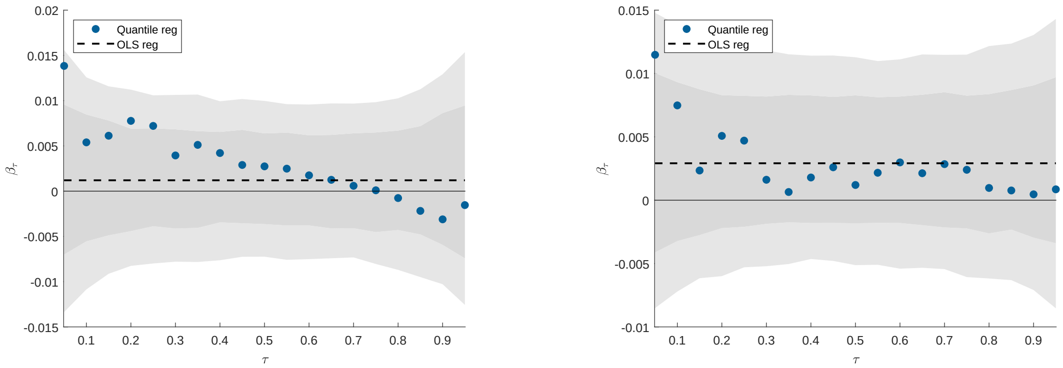


(a) 1Q ahead

(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 21: Coefficients on GPR

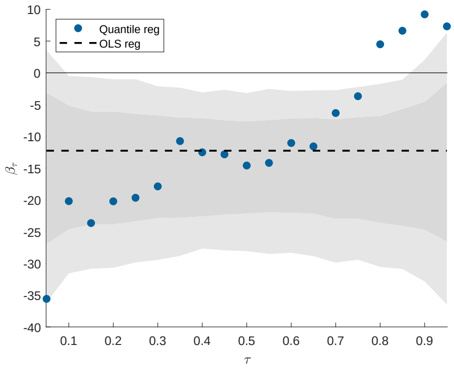


(a) 1Q ahead

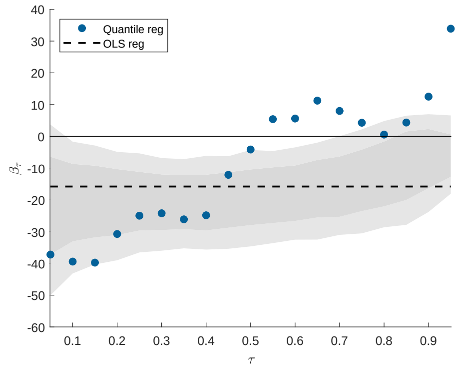
(b) 4Q ahead

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

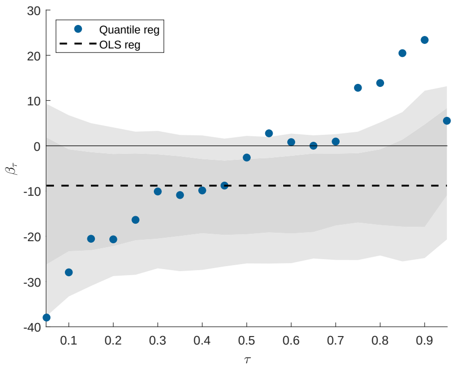
FIGURE 22: One-quarter-ahead coefficients on MACROU for France, Germany, Italy, and Spain



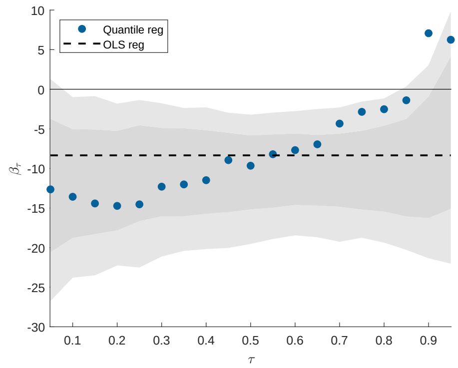
(a) France



(b) Germany



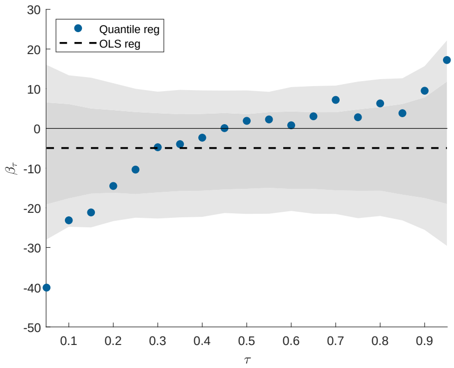
(c) Italy



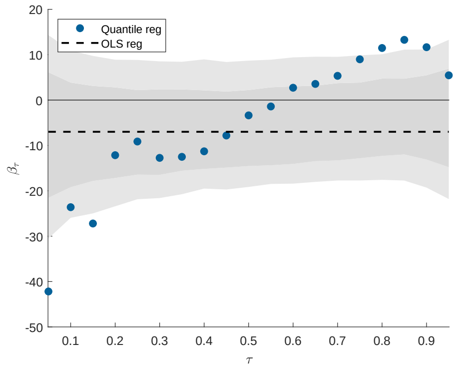
(d) Spain

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.

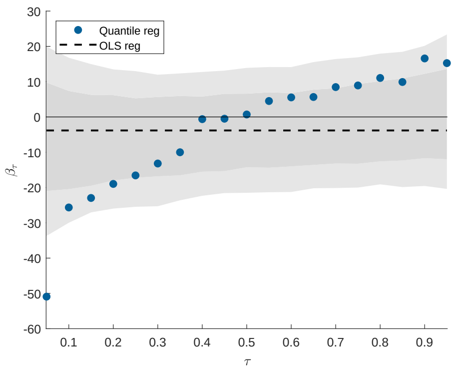
Figure 23: Four-quarter-ahead coefficients on MACROU: France, Germany, Italy, and Spain



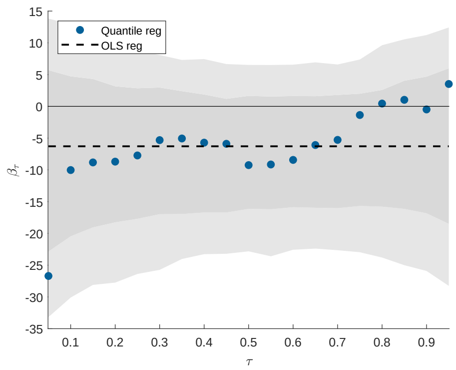
(a) France



(b) Germany



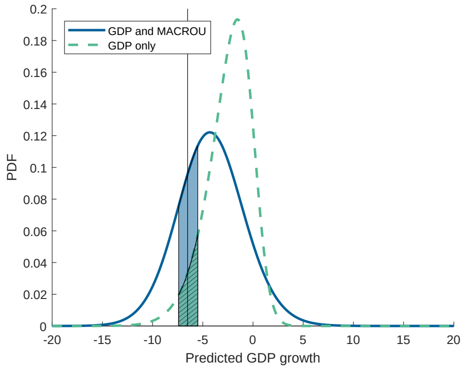
(c) Italy



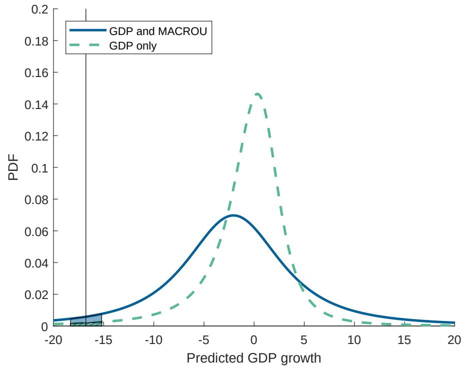
(d) Spain

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.

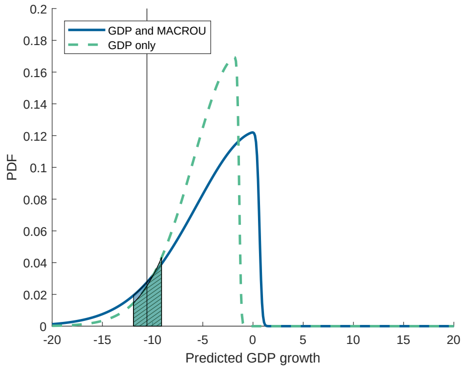
Figure 24: One-quarter-ahead predictive densities for 2009Q1: France, Germany, Italy, and Spain



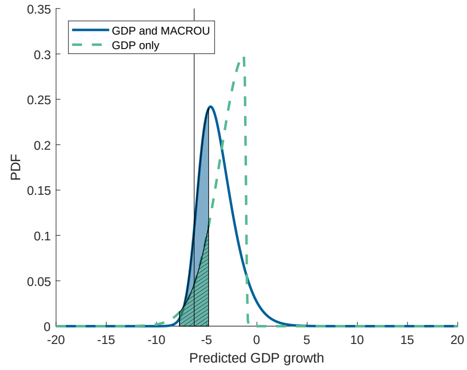
(a) France



(b) Germany



(c) Italy



(d) Spain

Notes: The sample period covers 1991Q2–2017Q4 for Germany and 1996Q3–2015Q4 for France, Italy, and Spain. The 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 indicates the cumulative probability within one standard deviation of growth around the outturn of the predictive density conditional on current growth and MACROU. The green shaded area (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 25: One-quarter-ahead coefficients on EPU: advanced economies

(a) Australia (b) Canada (c) France

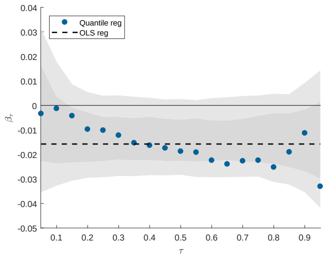
(d) Germany (e) Ireland (f) Italy

(g) Japan (h) Korea (i) Netherlands

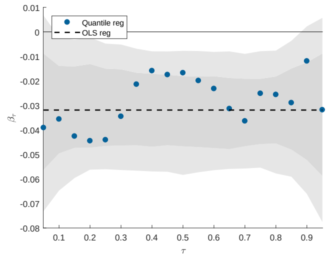
(j) Spain (k) UK (l) US

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.

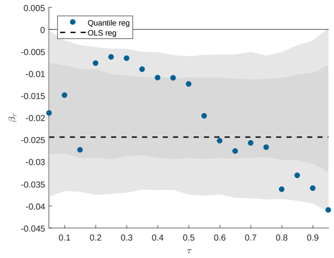
Figure 26: One-quarter-ahead coefficients on EPU: emerging market economies



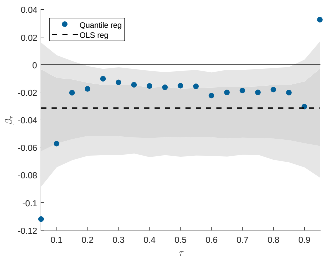
(a) Brazil



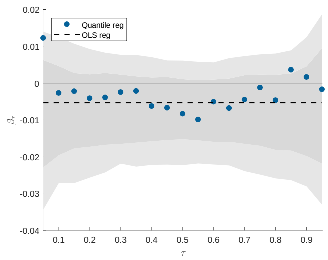
(b) Chile



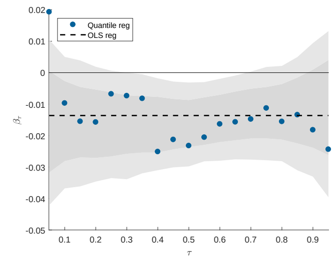
(c) China



(d) India



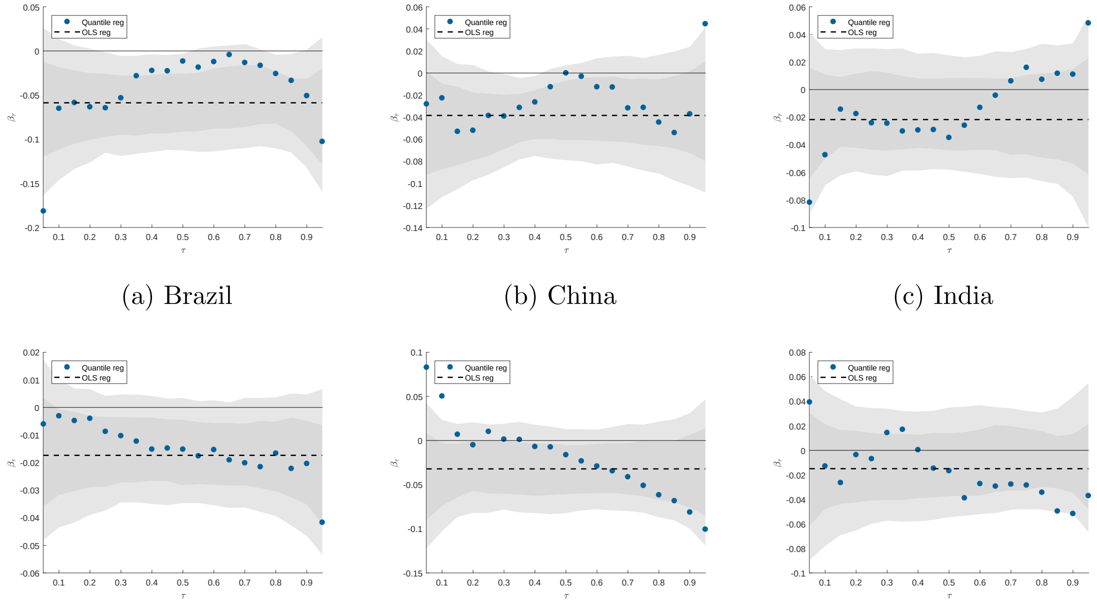
(e) Mexico



(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 27: 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

Table A.1: Summary statistics of GDP growth, MACROU, and 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

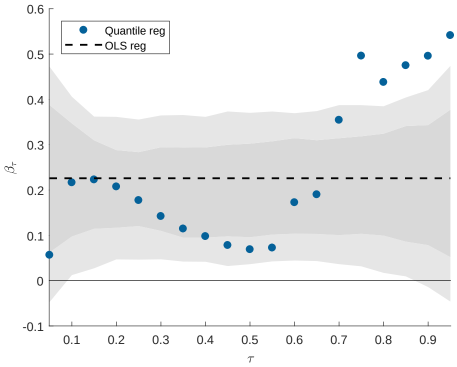
Notes: The sample period covers 1971Q1–2017Q4.

Table A.2: EPU sample period for each country

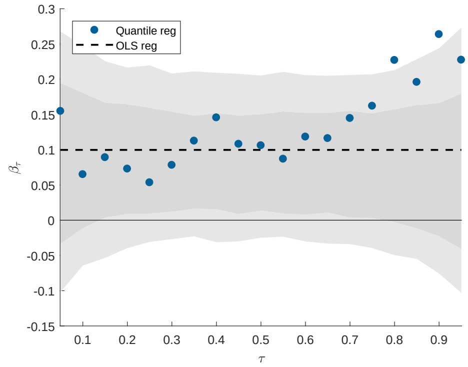
Country	Sample period
Advanced	
Australia	1998Q1-2017Q4
Canada	1985Q1-2017Q4
France	1987Q1-2017Q4
Germany	1993Q1-2017Q4
Ireland	1985Q1-2017Q4
Italy	1997Q1-2017Q4
Japan	1987Q1-2017Q4
Korea	1990Q1-2017Q4
Netherlands	2003Q2-2017Q4
Spain	2001Q1-2017Q4
UK	1997Q1-2017Q4
US	1985Q1-2017Q4
Emerging	
Brazil	1991Q1-2016Q4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



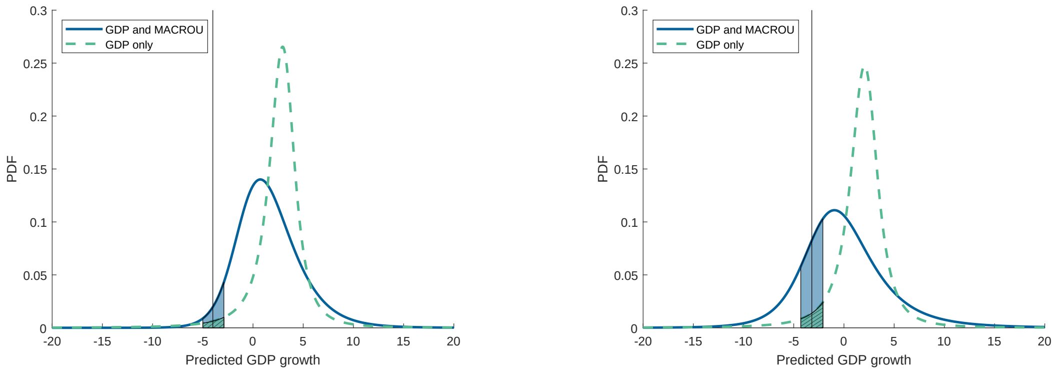
(a) 1Q ahead



(b) 4Q ahead

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

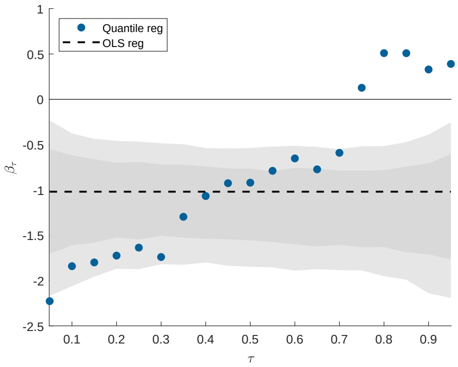
Figure B.2: Four-quarter-ahead predictive densities



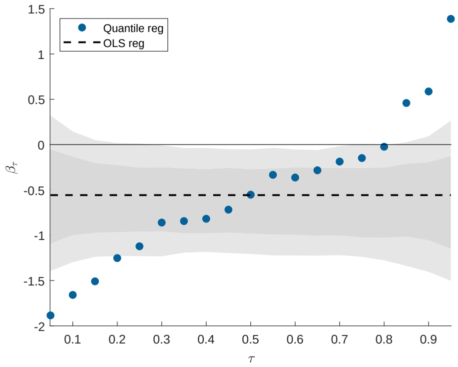
(a) 2009Q2 (b) 2009Q3

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 indicates the cumulative probability within one standard deviation of growth around the outturn of the predictive density conditional on current growth and MACROU. The green shaded area (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: Coefficients on FCI



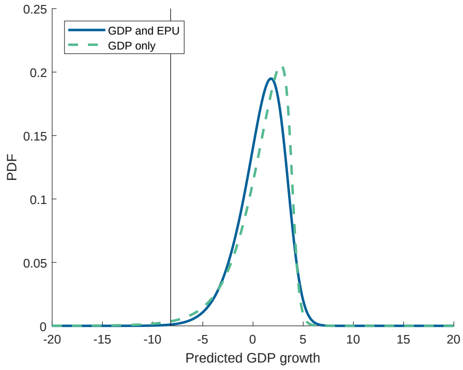
(a) 1Q ahead



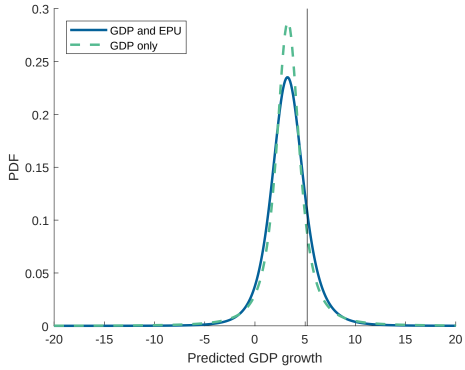
(b) 4Q ahead

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

Figure B.4: One-quarter-ahead predictive densities



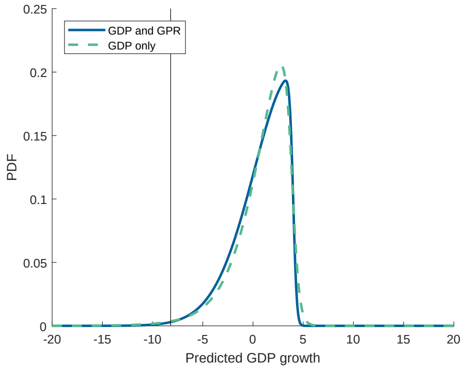
(a) 2008Q4



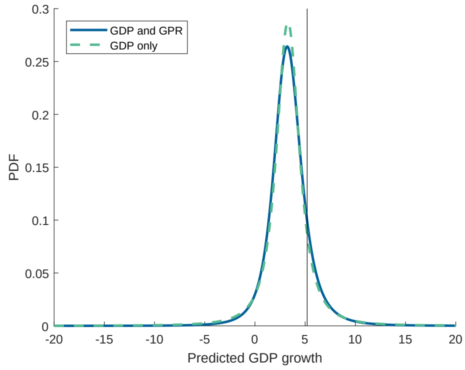
(b) 2014Q3

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.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.

Appendix C Additional Tables

Table C.3: Correlation between MACROU indexes in Europe

	France	Germany	Italy	Spain
France	1.00			
Germany	0.74	1.00		
Italy	0.76	0.49	1.00	
Spain	0.77	0.57	0.81	1.00

Notes: The correlation coefficients are calculated over 1996Q3–2015Q4.