When is Growth at Risk?*

Mikkel Plagborg-Møller[1], Lucrezia Reichlin[2], Giovanni Ricco[3], and Thomas Hasenzagl[4]

[1] *Princeton University*
[2] *London Business School, Now-Casting Economics, and CEPR*
[3] *University of Warwick, OFCE-SciencesPo, and CEPR*
[4] *University of Minnesota*

July 2, 2020

Abstract: This paper empirically evaluates the potentially non-linear nexus between financial indicators and the distribution of future GDP growth, using a rich set of macroeconomic and financial variables covering 13 advanced economies. We evaluate the out-of-sample forecast performance of financial variables for GDP growth, including a fully real-time exercise based on a flexible non-parametric model. We also use a parametric model to estimate the moments of the time-varying distribution of GDP and evaluate their in-sample estimation uncertainty. Our overall conclusion is pessimistic: Moments other than the conditional mean are poorly estimated, and no predictors we consider provide robust and precise advance warnings of tail risks or indeed about any features of the GDP growth distribution other than the mean. In particular, financial variables contribute little to such distributional forecasts, beyond the information contained in real indicators.

*We are grateful for very insightful comments from Mark Gertler, Domenico Giannone, Nellie Liang, Jim Stock and seminar participants at NYU. Plagborg-Møller acknowledges that this material is based upon work supported by the NSF under Grant #1851665. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the NSF.

Following the Great Recession, there has been an increasing interest in understanding the relationship between financial fragility and the business cycle. Having failed to predict the crash, the economics profession has been trying to understand what was missing in standard macroeconomic models and what are the key indicators of stress in financial markets which may help forecast crises and identify the build-up of macroeconomic risks ahead of time. The research agenda does not only involve prediction but also a revisitation of the earlier literature on financial frictions and the business cycle, pioneered by Bernanke and Gertler (1989), Kiyotaki and Moore (1997), and Bernanke et al. (1999), on the basis of the experience of the 2008 Great Recession.

This research goes beyond academia since it is potentially informative for macroprudential policy, which indeed focuses on the interaction between financial institutions, markets and the wider economy. Such policies need to be grounded in theoretical and empirical knowledge on what are the appropriate tools for strengthening the resilience of the financial system to macroeconomic shocks and *vice versa*. Early warnings of growth fragility would allow monetary and fiscal policy-makers to respond proactively to budding crises.

The structural literature has focused on two alternative classes of variables: those capturing the effect of an external financial premium (in line with models based on the financial accelerator) and those capturing balance sheet constraints such as household or bank credit, reflecting the idea that leverage is a main indicator of the accumulation of financial instabilities (see Gertler and Gilchrist, 2018, for a review).

Price variables such as credit spreads are typically used as proxies for the external financial premium. In fact, there is some consensus that measures derived from different types of interest rate spreads can have predictive power for future economic conditions. For the US, for example, the influential work of Gilchrist and Zakrajšek (2012) has proposed a measure of an excess bond premium that has been widely adopted in both academic and policy work.

A different but related line of research, pioneered by the BIS, has stressed the importance of the leverage cycle as an indicator of risk and used *excess private credit* as a measure of macrofinancial imbalances (see Basel Committee for Banking Supervision, 2010). Some studies have pointed at a correlation of excess growth in leverage and financial crises (see Jorda et al., 2011, Schularick and Taylor, 2012, Jorda et al., 2013 and related literature) and found that recessions preceded by financial crises are deeper and followed by slower recoveries (e.g. Reinhart and Rogoff, 2009, Laeven and Valencia, 2012 and related literature).[1] However, this literature is mainly concerned with long-term features of the nexus between finance and the macroeconony and on financial crises rather than recessions. At business cycle frequency, growth rates of credit aggregates are found to be pro-cyclical and lagging (see for example Giannone et al., 2019). In a recent paper, Brunnermeier et al. (2019) have pointed out that credit "moves passively with output" but that the negative correlation between credit spreads and output is mostly explained by the endogenous response of monetary policy.

Although the literature is very rich, few robust results have emerged from empirical studies about the extent to which financial variables can be used to predict economic activity. This confirms the conclusions of earlier work (see, for example, Stock and Watson, 2003, Forni et al., 2003 and Hatzius et al., 2010). In particular, three features of financial variables provide challenges to probing both the predictive and the causal relationships connecting them to the real variables. First, movements in financial variables are largely endogenous to the business cycle. Second, the dynamics of financial variables – and spreads in particular – are potentially non-linear and may be related to the higher moments of the GDP distribution rather than just the central tendency. Finally, there is a great degree of heterogeneity among financial indicators. Different types of financial variables capture different mechanisms through which financial markets and the macroeconomy interact.

The idea that financial and economic conditions may be correlated non-linearly has recently inspired a line of research which uses non-parametric methods in order to study the predictive distribution of GDP and its evolution in relation to financial conditions. Giglio et al. (2016) and Adrian et al. (2019) estimate the predictive GDP distribution conditional on a synthetic index of financial conditions. This index aggregates variables capturing financial risk, leverage and credit quality. For the US, such an index is constructed by the Chicago Fed (the National Financial Conditions Index, NFCI). Both papers, focusing on US data, found that the lower quantiles of GDP growth vary with financial conditions while the upper quantiles are stable over time, therefore pointing to an asymmetric and non-linear relationship between financial and real variables. New research is building on these ideas. Recent contributions are in Kiley (2018), Boyarchenko et al. (2019), Loria et al. (2019), Brownlees and Souza (2019), Figueres and Jarociński (2019), and Delle Monache et al. (2019).

[1] A related but different line of research has identified a financial cycle with different characteristics than the business cycle but leading it and found that financial cycle booms either end-up in crises or weaken growth (see Borio and Lowe, 2002 for early work and more recently Drehmann et al., 2012, Claessens et al., 2012 and many other papers).

As proposed by Adrian et al. (2018), the evaluation of the predictive GDP distribution can be used to define the concept of *growth at risk*, defined as the value of GDP growth at the lower fifth percentile of the predicted growth distribution, conditional on an index of financial stress. This concept has been adopted by policy institutions in many different countries to monitor risks (see, for example, Prasad et al., 2019 for a description of the use of this method at the IMF). The appeal of this approach to policy work, in particular macro-prudential, is that it provides a framework in which forecasting can be thought of as a risk managing exercise (see Kilian and Manganelli, 2008, for the first development of this idea).

The value of this framework for policy in practice rests on whether the dynamics of the moments of the conditional distribution of GDP can be captured with some degree of precision and on whether there is some out-of-sample predictability for moments other than the mean. In a recent paper, Reichlin et al. (2020) evaluate the out-of-sample performance of an aggregate indicator of financial stress and of some key financial variables for the GDP distribution, using the non-parametric approach of Adrian et al. (2019), and found little evidence of predictability beyond what can be achieved using timely indicators of the real economy. In this paper we broaden this analysis in several directions by asking three questions.

First, we want to assess the marginal role of financial variables in estimating and predicting the conditional distribution of GDP once we condition appropriately on available monthly macroeconomic information. Our conjecture is that monthly macroeconomic and financial variables co-move strongly at the contemporaneous level and that a large part of what is revealed by the NFCI reflects some joint information. This of course would not be the case if financial markets primarily reflected forward-looking information, a feature which cannot be assumed and must be tested.

Second, we want to evaluate whether non-linearities in the predictive distribution can be effectively exploited for forecasting and whether the dynamics of moments other than the mean can be precisely estimated. We believe that both evaluations are important for understanding whether the growth-at-risk framework can be used in practice for macro-prudential policy. The out-of-sample evaluation takes in consideration overall uncertainty: stochastic, estimation and model uncertainty. Parameter uncertainty – that is, uncertainty conditional on a particular assumed model – can be evaluated in-sample. For the first purpose we use the non-parametric method proposed by Giglio et al. (2016) and Adrian et al. (2019), while for the second purpose we use a fully parametric implementation of their approach. The motivation for using two different models is that the non-parametric approach very flexibly captures non-linearities without relying on particular functional forms, but, unlike the parametric method, it cannot easily be used to assess the statistical uncertainty surrounding the estimation of the moments of the growth distribution. We view the two approaches as complementary.

Third, we assess the potentially different roles of individual financial variables in estimating the moments of the conditional distribution by considering a variable selection algorithm. The motivation here is that – as has been observed by Reichlin et al. (2020) – financial variables have very different dynamic properties so that, by aggregating predictors into financial and real indices as done in the literature, some information can be lost. An approach that allows individual variables to enter the model in a flexible way may therefore be of interest. Moreover, understanding which specific economic variables carry information about the distribution of GDP growth would allow policy-makers and academics to hone in on specific mechanisms of growth fragility. We consider both U.S. data and a panel of twelve other OECD countries. This allows us to consider more than a few recessionary events in our sample. For the U.S., for which we have a richer data set, we perform the analysis both separately and in combination with other countries' data.

The overall conclusion of our analysis is pessimistic on the ability of the data to tell us something more than the evolution of the conditional mean. All other time-varying moments are imprecisely estimated. Moreover, both the out-of-sample analysis and the in-sample results point to very little additional predictive power of financial variables for other moments and for all moments at longer horizons. This remains true in a real-time nowcasting exercise where we take into account the timeliness of financial variables relatively to other data, since survey data are almost as timely and highly correlated with macroeconomic data. Finally, when single variables are allowed to enter flexibly in the model, these results are confirmed for both credit spreads (prices) and credit aggregates (quantities), although our methods cannot rule out that some interaction between spreads and credit is at work.

In a post-conference addendum, we run the real-time experiment over the recent COVID-19 lock-down episode in the first months of 2020. In this case, the model with financial variables does provide a more timely indication of the directional movement of the GDP growth distribution, relative to models that only condition on non-financial data. However, no model gets close to accurately predicting the severe magnitude of the downturn. Moreover, the COVID-19 episode has no bearing on the question of whether financial variables are helpful predictors outside very short forecast horizons.

At a more general level, our analysis confirms the older literature's results of the lack of predictive power of financial variables for the real economy, but we show that this finding carries over to an approach that in principle is capable of capturing non-linearities and tail risks. Our findings suggest that markets do not anticipate the timing of the recession and they price the risk only once they see it. In other words, the onset of a recession comes as a surprise to seemingly all agents in the economy. This blindness can be interpreted as revealing that information is rapidly available to all, but rare events such as recessions are fundamentally unforecastable. Importantly, our results do not imply that macro-prudential policy should give up on limiting the accumulation of financial fragilities, since it is likely that those fragilities amplify the damage to the real economy once recessions do occur. However, this is not a question that we can evaluate using the methods in this paper.

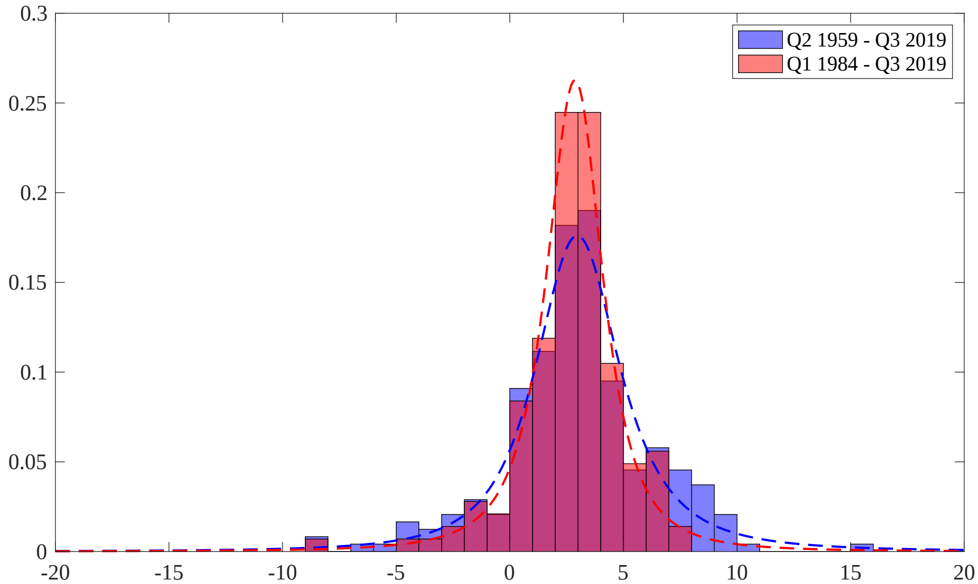
The order of the sections of the paper is organized around the questions we ask. After presenting some motivating facts in Section I, Section II asks the question of whether financial variables have specific forward-looking information that can inform an *out-of-sample* predictive relationship with the mean or higher moments of the GDP distribution. We also assess whether financial variables have predictive power for the GDP distribution during the *nowcasting* period, where we consider their timeliness advantage with respect to real economic indicators. Section III asks how precisely the moments of the predictive distribution of GDP growth, conditional on real and financial factors, can be estimated *in-sample*. As in Section II, we use as predictors both a *global* factor that includes joint real and financial information and a *financial* factor that includes the financial information orthogonal to the global factor. Section IV abandons the factor-based predictors and instead asks whether there are any specific individual economics variables that are able to explain the dynamics of GDP growth moments. As a case study, we evaluate the nowcast of the GDP growth distribution in the recent COVID-19 lock-down episode in Section V. Section VI concludes.

I. A Few Motivational Facts

In this section we present a few facts that motivate the analysis of the paper.

Fact 1: Economic fluctuations are asymmetric over the business cycle. Figure 1 shows that the distribution of U.S. GDP growth exhibits some skewness and fat tails. The figure plots the histograms of annual real GDP growth over the samples 1959Q2-2019Q3 (in blue) and 1984Q1-2019Q3 (pink) and the associated fitted distributions. The dark red area describes the overlapping segments. Growth in both subsamples exhibits skewness and heavy tails, although arguably to varying degrees. Indeed the literature has suggested that recessions can be described as a combination of a negative first-moment (mean) shock and a positive second-moment (uncertainty)

Figure 1: Annual real GDP growth.[a]



Sources: FRED-QD and authors' calculations.

[a] Histograms of annual real GDP growth over the samples 1959q2-2019q3 and 1984q1-2019q3. The fitted distribution are computed by adopting the flexible skew-t distribution developed by Azzalini and Capitanio (2003).

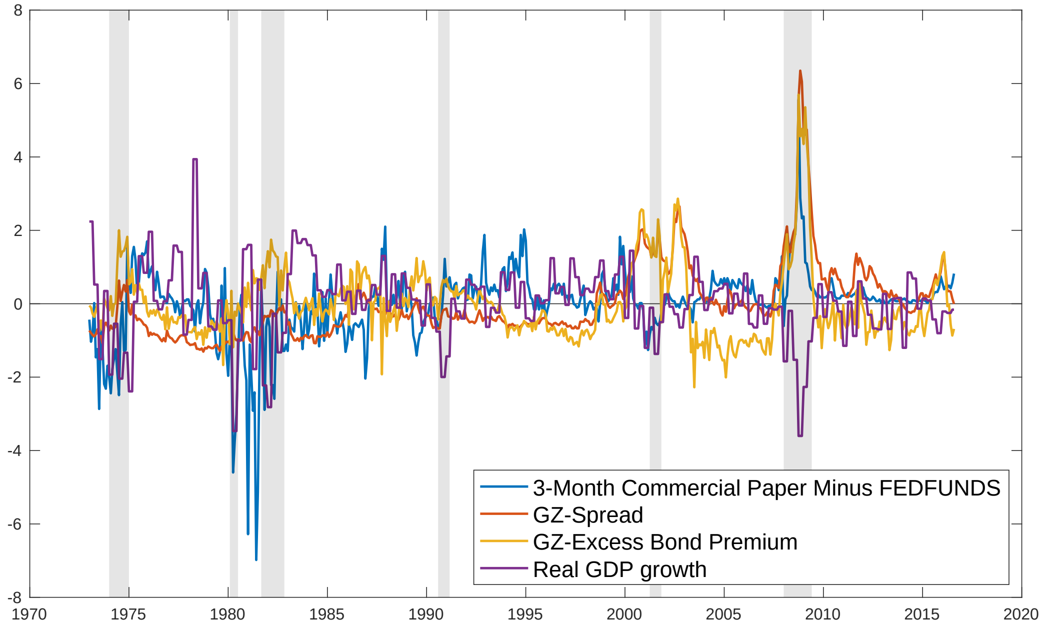
shock (e.g., Bloom, 2014) or as negative third-moment (skewness) shocks (e.g., Bloom et al., 2016), and fat tails have been found to be a feature of GDP distribution in many advanced economies (see, for example, Fagiolo et al., 2008).

This fact motivates an analysis which is based on estimation and forecasting of moments other than the mean of the predictive GDP distribution.

Fact 2: Financial condition indicators and spreads are highly negatively correlated with output growth at the time of recessions. Figure 2 shows a clear negative correlation between spreads and GDP growth around recessions (although the relation is unstable over the sample). The figure plots quarterly annualized GDP growth for the period from 1973q1 to 2015q1 against three credit spreads that have been considered in the literature as measures of financial risk (see Gilchrist and Zakrajšek, 2012).

This chart suggests that the asymmetry in the business cycle for output growth is associated with the asymmetry in the behavior of credit spreads. The latter increase sharply in coincidence or just prior to an economic contraction, while there is no symmetric movement in these variables during booms. The intriguing suggestion is that, by conditioning on these variables, it would be possible to capture higher

Figure 2: Financial stress indicators and GDP growth rates.[a]



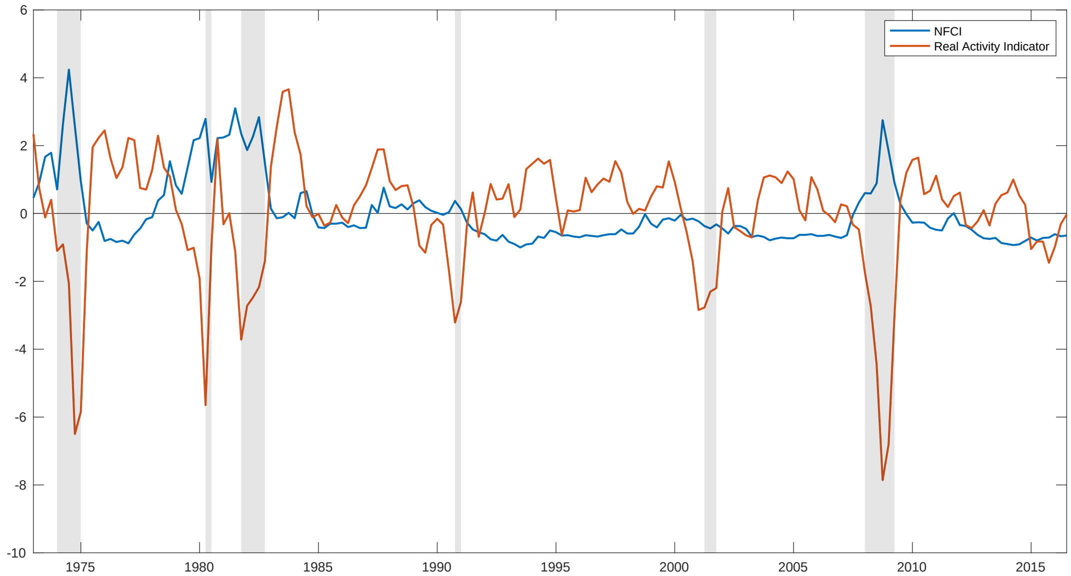
Sources: FRED-MD, FRED-QD, and Gilchrist and Zakrajšek (2012).

[a] 3-Month Commercial Paper minus Federal funds rate spread, Gilchrist and Zakrajšek (2012) spread and excess bond premium, and real GDP growth from 1973q1 to 2016q3.

moments of the GDP conditional distribution. As discussed in the Introduction, this idea has been the inspiration for the literature that has explored the predictive power of financial variables for moments other than the mean, and which we seek to evaluate in this paper.

Fact 3: Movements in financial indicators are largely endogenous and related to output growth. Financial time series and macroeconomic variables share a pronounced contemporaneous common component. Figure 3 reports the quarterly average of the monthly Chicago Fed's National Financial Conditions Index (NFCI)

Figure 3: Business cycle and financial condition indices.[a]



Sources: authors' computation.

[a] The chart plots an index of real activity extracted as a common factor from a large set of macroeconomic variables and excluding financial variables against the Chicago Fed's National Financial Condition Index (NFCI). The time sample is 1975q1 to 2015q1.

and of a business cycle index computed from a large set of monthly macroeconomic indicators.[2,3,4]

The two synthetic aggregate indicators of financial and macroeconomic variables exhibit a very clear pattern of comovement. The strong correlation emerging from the plot indicates that movements in financial indicators are possibly endogenous and contemporaneous to business cycles fluctuations.

[2]The business cycle index is computed as the first common factor to all of the variables in the FRED-MD dataset, except the ones classified as financial. Appendix S.A and Appendix S.B provide details on the estimation of the factor.

[3]The NFCI index is a synthetic indicator computed as a common factor extracted from 105 mixed-frequency – weekly, monthly and quarterly – financial variables. It averages four categories of data: credit quality, risk, non-financial and financial leverage. All variables are transformed to stationarity and standardized. For a description of the NFCI (variables considered and methodology), see Brave and Butters (2012) and the Chicago Fed's dedicated website: `https://www.chicagofed.org/publications/nfci/index`. Both factors are estimated by maximum likelihood following Doz et al. (2012) and averaged across quarters.

[4]Table S.4 in the Appendix reports the full set of the estimated values for the model coefficients.

Figure 4: Heterogenous dynamics of financial indicators.[a]

Sources: FRED-QD.

[a] Chicago Fed's National Financial Condition Index (NFCI) underlying components from 1973q1 to 2015q1.

This fact suggests that, in order to establish the role of financial variables for predicting the GDP distribution, one should control for the common and contemporaneous component (what we define as the "global factor") and focus on the additional "marginal" information available in the financial indicators (the "financial factor"). This is what our analysis will do.

Fact 4: Different types of financial variables have heterogenous dynamics along the business cycle. Figure 4 provides a more disaggregated view of financial stress by plotting the NFCI and its components. The chart suggests that the NFCI aggregates components with heterogeneous dynamic characteristics, potentially reflecting different forms of fragility in the financial system. It shows that the aggregate NFCI dynamics reflect mainly the risk and credit components, while non-financial leverage follows a smoother cyclical pattern, and financial leverage exhibits some higher-frequency idiosyncratic dynamics.

Indeed, different indicators of stress capture different aspects of financial frictions, which may be relevant at different moments in time – either preceding, contemporaneous to, or following the financial crisis (see Bernanke, 2018 for an analysis of the 2008 recession in the U.S.).

This fact motivates our analysis of the role of individual variables in predicting the moments of the conditional distribution of GDP growth.

II. Predicting Growth at Risk

In this section we assess whether financial variables aggregate forward-looking information that helps predict the distribution of future GDP growth. In particular, we are interested in teasing out information about the future path of output and its moments *in excess* of the contemporaneous information provided by other macroeconomic indicators. Toward this aim, we consider the marginal gain in the predictive distributions for GDP growth (and its moments) when financial-specific information is incorporated, relative to baseline models that only condition on the *global* common component in real and financial data.

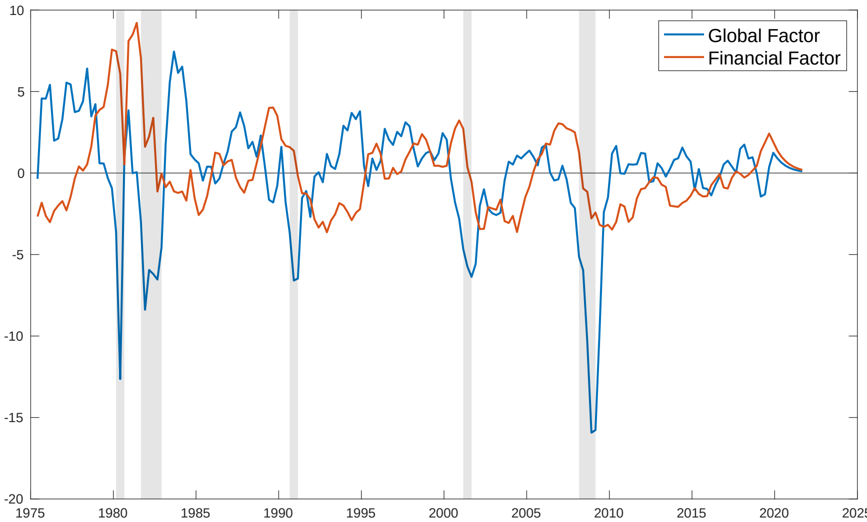
We provide both an out-of-sample exercise – one and four quarters ahead – and a fully real-time monitoring of risks to GDP growth with a realistic data release calendar, encompassing macroeconomic and financial variables. It is worth observing that the out-of-sample exercise provides an overall summary of the performance of the model by factoring in several types of uncertainty, excluding the uncertainty about data itself that is a component of the flow of revised data releases. The real-time exercise takes the latter dimension of uncertainty partially into account since it is based on a realistic calendar of data releases mimicking the information flow.

The results are overall negative. The inclusion of financial-specific information does not improve the mean squared forecast error of the model, nor does it help capture the dynamics of any of its moments. However, financial variables appear (very marginally) to help in pinning down the common contemporaneous information, in real time.

II.A. The Evolution of Out-of-Sample Growth Moments

We first ask the following questions: How do the moments of the predictive distribution vary over time? Do financial variables capture shifts in the predictive mean, variance, or higher moments of the GDP distribution? Is it possible to predict an increase in GDP growth vulnerability out of sample? This exercise focuses on short-to-medium horizons and tries to gauge the overall abilities of the models in assessing risks to GDP growth. Importantly, while providing an assessment of the models' performance against the several sources of uncertainty – stochastic, estimation and model uncertainty – it abstracts form the data uncertainty that characterizes data

Figure 5: Global and financial factors.[a]



Sources: authors' computation.

[a] The Global and Financial factors, for the period from 1975q1 to 2019q3.

releases in real time. We integrate this last source of uncertainty in the subsequent real-time exercise.

DATA AND MODEL The first step in our exercise is the estimation of common factors from a large panel of variables. Specifically, we extract two indices of *commonalities*. The first factor, which we refer to as the *global factor*, is common to all the variables in the McCracken and Ng (2016) FRED-MD dataset, including real, financial, monetary, and price variables. The second factor, which we refer to as the *financial factor*, is only common to the financial variables and is by definition orthogonal to the global factor. Figure 5 plots the two factors over the sample period. Appendix S.A provides details on the factor models adopted to estimate the factors.[5] Table S.1 in Appendix S.B provides details on the dataset and on the assumptions adopted to estimate the factors.

The key difference from the analysis of Adrian et al. (2019) is that, while they adopt the NFCI as the main indicator of financial conditions, we separate the information contained in the global factor and the orthogonal financial factor. Reichlin et al. (2020) observe that the NFCI is largely endogenous to economic conditions in the U.S., and that it has high correlation with a factor extracted from non-financial

[5] Figure S.1 in Appendix S.C reports the estimated loadings for the factor model with a global and a financial factor.

variables only (as also shown in Figure 3). This observation motivates our choice to adopt a global indicator of economic conditions as well as a financial-specific factor that could, in principle, capture independent forward-looking information about the moments of the predictive distribution of GDP growth that is not obtainable from current economic conditions.

We employ the factors as predictors in the non-parametric quantile regression framework of Adrian et al. (2019). To compare the predictive content of the two factors, we consider three empirical specifications. We model annualized cumulative GDP growth at the one-quarter-ahead and four-quarter-ahead horizons as being driven by, respectively:

(*model 1*) GDP growth at time t;

(*model 2*) GDP growth at time t and the economic activity global factor at time t;

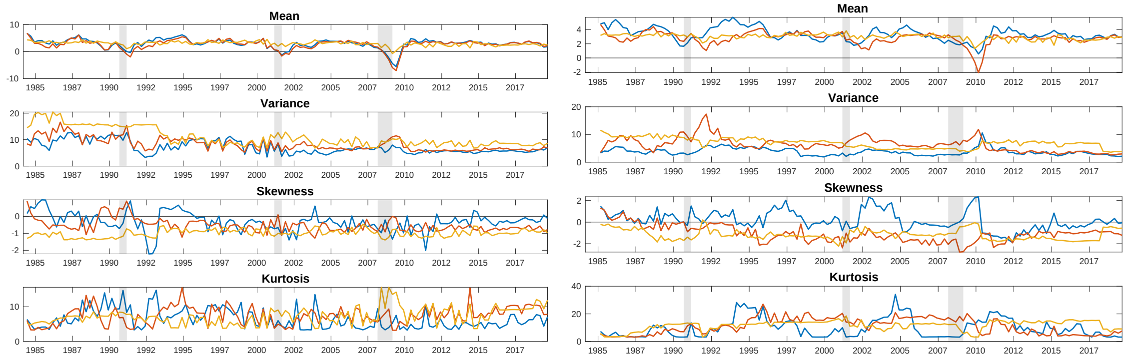
(*model 3*) GDP growth at time t and both the global and the financial factors at time t.

We first estimate the factor model using data from 1975q3 to 1984q1. We then iteratively estimate the predictive distributions of GDP growth one and four quarters ahead, expanding the estimation sample, one quarter at a time, until the end of the sample in 2019q3. In every quarter of the out-of-sample period, we apply the non-parametric prediction approach of Adrian et al. (2019). This involves first estimating the relationship between the percentiles of future GDP growth and the predictors using quantile regressions. Then we smooth out the predictive distribution by fitting a flexible family of distributions to the estimated conditional percentiles, allowing for both skewness and heavy tails. The details of the prediction procedure are described in Appendix S.A.

RESULTS Regardless of the predictors used, the models fail to provide noticeable advance out-of-sample signals of the likelihood or severity of recessions. Figure 6 shows the first four moments of the forecast distribution of GDP growth at horizons $h = 1$ and $h = 4$. By breaking down the predictive distribution into different moments, we aim to show what features of the distribution of GDP growth are predictable, if any. The figure compares the models that condition on (i) the global factor, the financial factor, and GDP (blue line), (ii) the global factor and GDP (red line), and (iii) lagged GDP only (yellow line).

At the one-quarter-ahead horizon ($h = 1$) shown in panel (A), the distributions of both models that incorporate factors show a sharp decrease in the mean around the period of the Great Recession, but importantly, the model incorporating the

Figure 6: Out-of-sample forecasts: Time evolution of the predictive distribution of GDP growth.[a]



Sources: authors' computation.

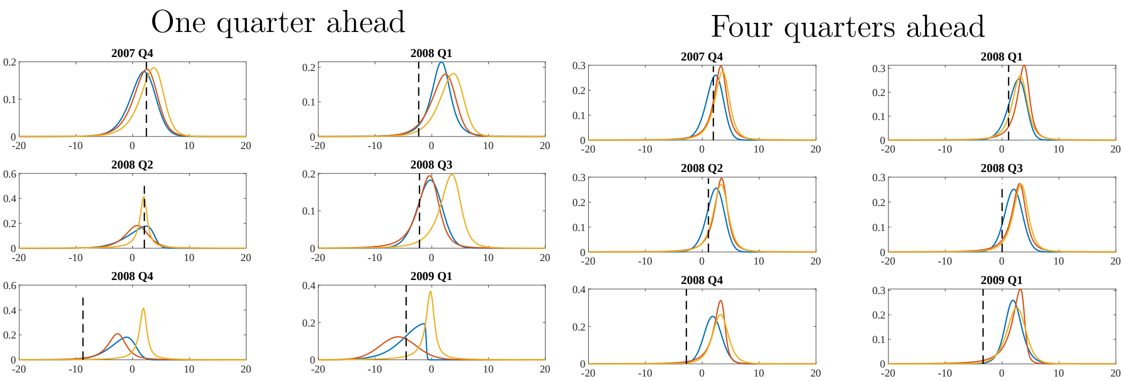
[a] Time evolution of the four moments of the one-quarter ahead predictive distribution of GDP growth, from 1993q1 to 2015q4, for the models including (i) the Global factor, Financial factor, and GDP (blue), (ii) the Global factor and GDP (red), and (iii) GDP only (yellow).

financial factor does not seem to have an informational advantage. Strangely, the model not incorporating the financial indicator seems to capture an increase in the variance related to the Great Recession, albeit with some delay. In fact, the movement in the variance lags the 2008 recession by a few quarters and it results from the incorporation into the model, with a quarter of delay, of the spike in spreads in the fourth quarter of 2008. Also, the increase is not remarkable when compared to the level of the forecast variance in the '90s. Skewness and kurtosis apparently move over the sample but with patterns that are not easy to interpret or to relate to economic contractions.

At the four-quarter-ahead horizon ($h = 4$) shown in panel B, the findings are in line with those discussed for $h = 1$ but the reactions to contractions are even more delayed. Interestingly, only the model with the global factor forecasts substantial contractions in GDP at the four-quarter horizon around recessionary periods, although with long delay. Higher moments do not exhibit interpretable patterns. This raises doubts about the ability of the models to correctly capture the dynamics of these moments, at least out-of-sample, an issue we will return to in Section III.

We now zoom in on the Great Recession period. Figure 7 reports the two predictive distributions at different points in time, for $h = 1$ and $h = 4$, before and during the Great Recession (2007q4-2009q1), for the three different models. None of the models seem to predict the crisis. At horizon $h = 1$, panel (A) shows that all

Figure 7: Out-of-sample forecasts: Predictive distributions during the Great Recession.[a]



Sources: authors' computation.

[a] Quarter by quarter evolution of the predictive distributions in the period of the Great Recession, from 2007q4 to 2009q1, for the models including (i) the global factor, financial factor, and GDP (blue), (ii) the global factor and GDP (red), and (iii) GDP only (yellow). The charts report also the realization of annualised GDP growth one and (cumulative) four quarters ahead, respectively.

the models fail to capture the onset of the economic downturn in 2008q1, and they all assign a low probability to it. As financial stress spikes up in the fourth quarter of 2008, the conditional forecast of both models that include the global factor fans out, attaching higher likelihood to a wider range of events. At horizon $h = 4$, panel (B) shows that all models seem to do equally bad in capturing the shift in economic conditions. Although the model that only conditions on lagged GDP performs particularly poorly, the two models incorporating factors yield very similar predictive distributions. Indeed, the model that also incorporates financial variables seems to have little informational advantage.

A more systematic evaluation of the distributional forecast accuracy by analysing the models' *predictive scores* confirms the minuscule predictive content of the financial factor. This is shown in Figure S.2 in Appendix S.D. The predictive score is high if a model attaches a high likelihood to the value of GDP growth that is actually realized (see the formal definition in Appendix S.A). While at $h = 1$ the two models have nearly indistinguishable predictive scores, at $h = 4$, the model incorporating the financial factor seems to have a very small advantage over the model with the global factor only. Yet its performances do not uniformly dominate the second model, over the sample.

SUMMARY An explorative out-of-sample analysis indicates that financial variables help only very marginally in improving the performance of a model that already includes a real activity indicator, computed as the common factor of a large panel of real macroeconomic variables. Interestingly, the movements in higher moments of the forecast seem to not be very informative.[6] In particular, skewness and kurtosis do not show any interpretable movement around recessions. This suggests that growth vulnerability is a story about the mean and possibly volatility of growth, rather than about time-variation in the probability of extreme events. We return to this issue in Section III, where we will be able to characterize the statistical uncertainty associated with the estimation of each time-varying moment. In the next subsection we explore the specific informational content of financial indicators and their relations with real variables, their timeliness, and the heterogeneity across financial variables.

II.B. Real-Time Monitoring of Risks to Growth

To assess the predictive ability of the quantile regression model in real time, we now turn to *nowcasting*, i.e., predicting the current-quarter value of GDP growth ($h = 0$). We will also continue to consider the one-quarter-ahead forecast horizon ($h = 1$). Although these horizons are too short-term for the practical implementation of macro-prudential policies, they are relevant for prediction since the literature has shown that, generally, there is very little predictability for the mean of GDP growth beyond one quarter (see, for example, Giannone et al., 2008). Additionally, monetary and fiscal policy may be able to respond within the quarter in some cases. Finally, our results so far seem to indicate that the model has limited predictive ability at longer horizons anyway.

DATA AND MODEL In this exercise we update the factors and hence the forecast and nowcast in relation to a calendar of data releases, in the tradition of the nowcasting literature. First, we construct a set of real-time data vintages from the ALFRED database. The data series that we include were chosen to closely resemble the FRED-MD dataset, given data availability constraints of the real-time data. The real-time vintages for some variables only become available after the beginning of the forecasting exercise. Those variables are added to the exercise once they become available. As we did above, we extract a number of common factors from those vintages. Beyond the global factor (common to all the variables) and the financial factor (common to the financial variables only and orthogonal to the global factor),

[6]This is consistent with the findings of Adrian et al. (2019).

Table 1: Groups of variables used in the nowcast exercise and their release lags.[a]

Variable Group	Release lag
Stock Indices, Exchange Rates, Interest Rates, and Spreads	1
ISM Indices	1
Employment & Earnings	5
Monetary Aggregates	15
IP & subcomponents	16
CPI, PPI & subcomponents	16
Housing Starts, Housing Permits & subcomponents	18
Personal Consumption Expenditure & Real Personal Income	30

[a] The lag variable is the approximate number of days between the last day of the reference month and the date at which the variable becomes available.

we also consider a *non-financial* factor, computed from the subset of the data set that excludes financial variables.

The calendar of data releases uses the average release lag for each variable. In the out-of-sample exercise, we then iterate over the release calendar, position ourselves at each release date, and perform the following three-step procedure:

(*Step 1*) We estimate the factors using an EM algorithm. Then we average the monthly factors to get quarterly factors.

(*Step 2*) We apply the nonparametric forecast approach of the previous subsection to quarterly data up to the current quarter. Using this approach, we construct predictive distributions for current-quarter and next-quarter GDP growth.

We consider the following three sets of predictor variables.

(*model 1*) Global factor only;

(*model 2*) Global factor and financial factor;

(*model 3*) Non-financial factor only.

We construct quarterly versions of the factors as averages of the factors estimated in a monthly nowcasting model (see Giannone et al., 2008). We begin the out-of-sample forecasting exercise in 2005Q1. For each data release we estimate the factors and the quantile regression parameters using an expanding data set starting in 1980Q1.

Some of the financial variables included in our real-time exercise – i.e. stock indices, oil price, exchange rates, interest rates, and spreads – are available at daily or higher frequency. However, they enter the model only as end-of-the-month values on the first day of the following month. This, while being a blunt approximation of the information flow, still affords these financial variables an informational advantage by including them in the model before any real and nominal variable, for the month of interest. Table 1 shows the average lag of the release of the most important groups of variables that we use in the exercise. Table S.1 in Appendix S.B shows all the variables included in the dataset, their average release lag, and the factors on which they load. By employing the growth-at-risk framework, our methodology also allows for financial variables to affect higher moments of the GDP forecast, which could be particularly important in determining tail risks.

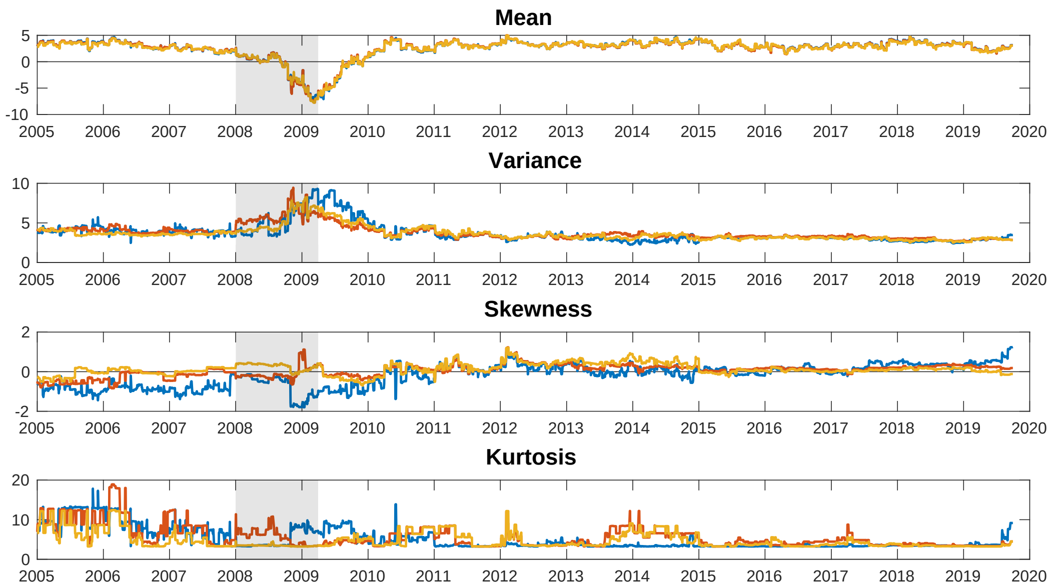
Comparing the short-term forecasting performance of a model that contains only the global factor and a model that contains both the global and financial factors allows us to study the additional information content of financial variables over and above what is common to all the other economic variables. Additionally, comparing the short-term forecasting performance of the model that contains only the non-financial factor helps assess the effects of financial variables on imputing the global factor.

RESULTS Financial variables help only very marginally for nowcasting, and only because they help to estimate the global factor more precisely. Figure 8 reports the evolution over time of the four moments of the predictive growth distribution at horizon $h = 0$. The top panel shows that the conditional means of the predictive distributions in all models are nearly identical. The global factor captures the co-movement between all variables, including the financial variables, and adding the orthogonal financial factor does not have a substantial effect on the mean of the predictive distribution. The model with the factor estimated using only non-financial variables provides a forecast for the mean that is nearly identical to the other models'.

The models disagree more about the variance, skewness, and kurtosis of the predictive distributions. For example, in the middle of the Great Recession, the model with the financial factor shows a sharp spike in skewness and kurtosis in the density nowcast for the first quarter of 2009. This is an indication that the real-time model that incorporates financial variables may capture some downside risks to growth, although with a delay.

Figure 9 shows that the early availability of financial variables does not translate into more accurate forecasts of the mean of the GDP distribution at short horizons. The top panel of the chart reports the root mean squared forecast error of the three models, which depends only on the mean of the predictive distributions, as a function of the remaining time until data on GDP growth is released. We make the following observations: (i) The root mean squared forecast errors of all three models are on a slightly downward-sloping path throughout the forecasting period. This

Figure 8: Nowcast of the moments of GDP growth.[a]



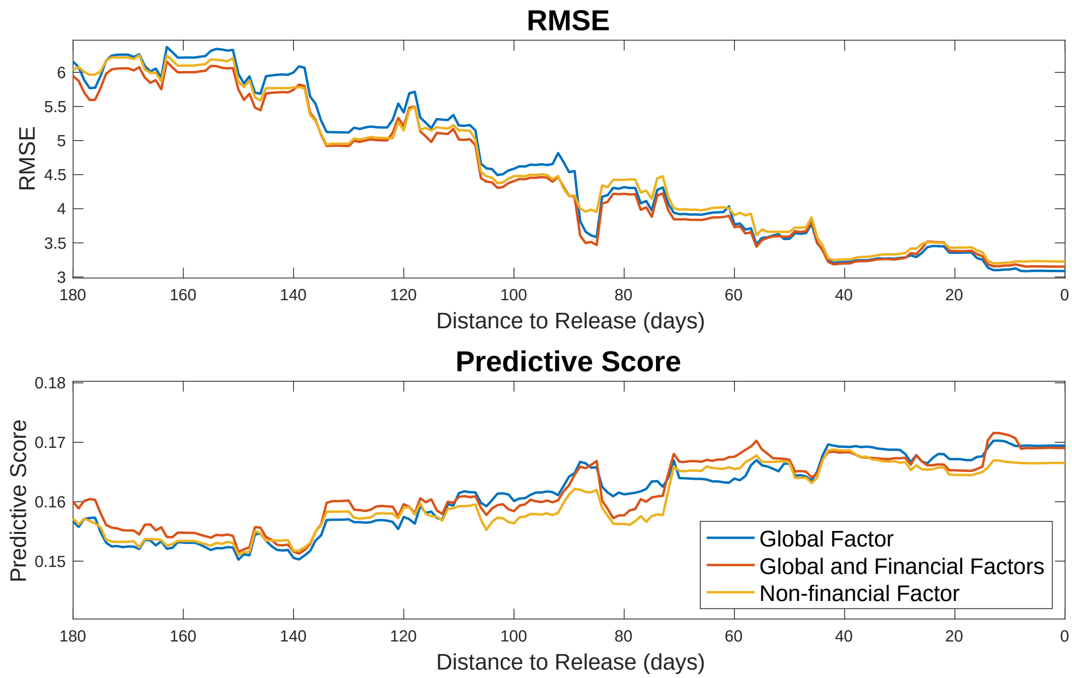
Sources: authors' computation.

[a] Time evolution of the four moments of nowcast predictive distribution of GDP growth at $h = 0$ of quantile regressions with (i) the global factor only (blue line), (ii) the model with the global and financial factors (red line), and (iii) the model with the factor estimated using only non-financial variables (red line) from 2005q1 to 2019q3.

indicates that the data released over the forecasting period marginally improves the forecasting performance of the model. (ii) The root mean squared forecast errors of models 1 and 2 are nearly identical, which indicates that including the orthogonal financial factor into the model does not improve the ability to forecast the mean of the growth distribution. (iii) Although the financial variables could in principle still help by providing timely information about the global factor, this contribution is only marginal, as is evident by comparing the root mean squared forecast errors of models 1 and 2 (which use financial data) versus model 3 (which does not). This is also apparent from the bottom panel of the figure, which shows the predictive scores of the three models. This measure accounts for the accuracy of the entire predictive distribution of GDP growth, not just the mean. Only an ever so slight improvement of the forecasting performance of models 1 and 2 (which use financial data) over model 3 (which does not) is noticeable.

SUMMARY Our out-of-sample test of the predictive ability of a nowcasting model in which we augment the standard global factor with an orthogonal financial

Figure 9: Nowcast evaluation.[a]



Sources: authors' computation.

[a] Top panel: Root mean squared error of the nowcast predictive distribution of GDP growth. Bottom Panel: Predictive score of the nowcast predictive distribution of GDP growth. Both charts show the values over the 1984q1 to 2019q3 sample, averaged of the distance to the release data of GDP.

factor reaches a disappointing conclusion: The performance of the model with both the global and financial factor is largely indistinguishable – in terms of root mean squared forecast error and predictive score – from a model with only the global factor. The inclusion of financial variables into the global factor does lead to a small improvement in predictive score relative to a model with only a non-financial factor. This is probably due to the timeliness of financial variables, which can provide marginally earlier updates to the expected path of GDP growth at very short horizons.

III. How Does the Distribution of GDP Growth Change Over Time?

The previous section demonstrated that there may be some limited out-of-sample information about the time-varying forecast distribution of GDP growth, although most of the predictive information comes from a global factor, not specifically financial variables. However, the method used there did not allow us to quantify the uncertainty surrounding any putative time-variation in the conditional moments. In this section, we estimate a full statistical model of post-1975 U.S. GDP growth that allows conditional moments to vary flexibly over time. Crucially, we will be able to quantify the uncertainty about the parameters in the model and thus the implied uncertainty about the evolution of the conditional moments of GDP growth. Unlike the previous section, we focus on *in-sample* results in this section. Thus, the only uncertainty is about the parameters of the model, which is assumed to be correctly specified. Even then, we find that the data is only informative about the conditional mean; the time-variation of the conditional variance and higher moments is very imprecisely estimated. As a result, the time-variation in the conditional recession probability and in the potential severity of recessions is driven almost exclusively by movements in the mean.

III.A. Data and Model

We model quarterly GDP growth as being driven by lagged GDP growth, as well as the global and financial factors estimated in Section II. We use the final estimates of these factors. In this section we merely use these factors as a convenient set of low-dimensional explanatory variables, whereas the next section will attempt to attribute any explanatory power to individual variables with more direct economic interpretation. The sample period for estimation is 1975q2–2019q2. Appendix S.E runs various benchmark linear forecast regressions using the global and financial factors. These benchmark regressions reveal that both factors potentially could contribute to the mean forecasts, at least in sample. However, we are primarily interested in going beyond the mean.

We assume that the one-quarter-ahead conditional distribution of GDP growth is given by the flexible *skew-t* distribution developed by Azzalini and Capitanio (2003). The distribution is indexed by four parameters: location μ, scale σ, shape α, and heavy-tailedness ν. These parameters influence – but do not directly equal – the conditional mean, variance, skewness, and kurtosis of the distribution. If $\alpha = 0$, the distribution reduces to the usual symmetric Student-t distribution with ν degrees of freedom, which in turn reduces to the normal distribution when $\nu \to \infty$. If $\alpha > 0$, the distribution is positively skewed (higher probability of above-average growth than of below-average growth), while $\alpha < 0$ implies the opposite. Smaller values of ν correspond to fatter tails of the growth distribution (higher probability of abnormally low or high growth).

To allow the explanatory variables to influence several features of the GDP distribution, we model the location parameter $\mu = \mu_t$, the logarithm of the scale parameter $\log \sigma = \log \sigma_t$, and the shape parameter $\alpha = \alpha_t$ as being *time-varying*. These parameters are each assumed to depend linearly on an intercept, lagged GDP growth, and the lagged global and financial factors. The heavy-tailedness parameter ν is constant over time. This parameter mainly influences the kurtosis of the conditional growth distribution, and we will show below that there is little information in the data about time-variation in higher moments anyway. We apply a Bayesian estimation procedure with weakly informative priors on the parameters.

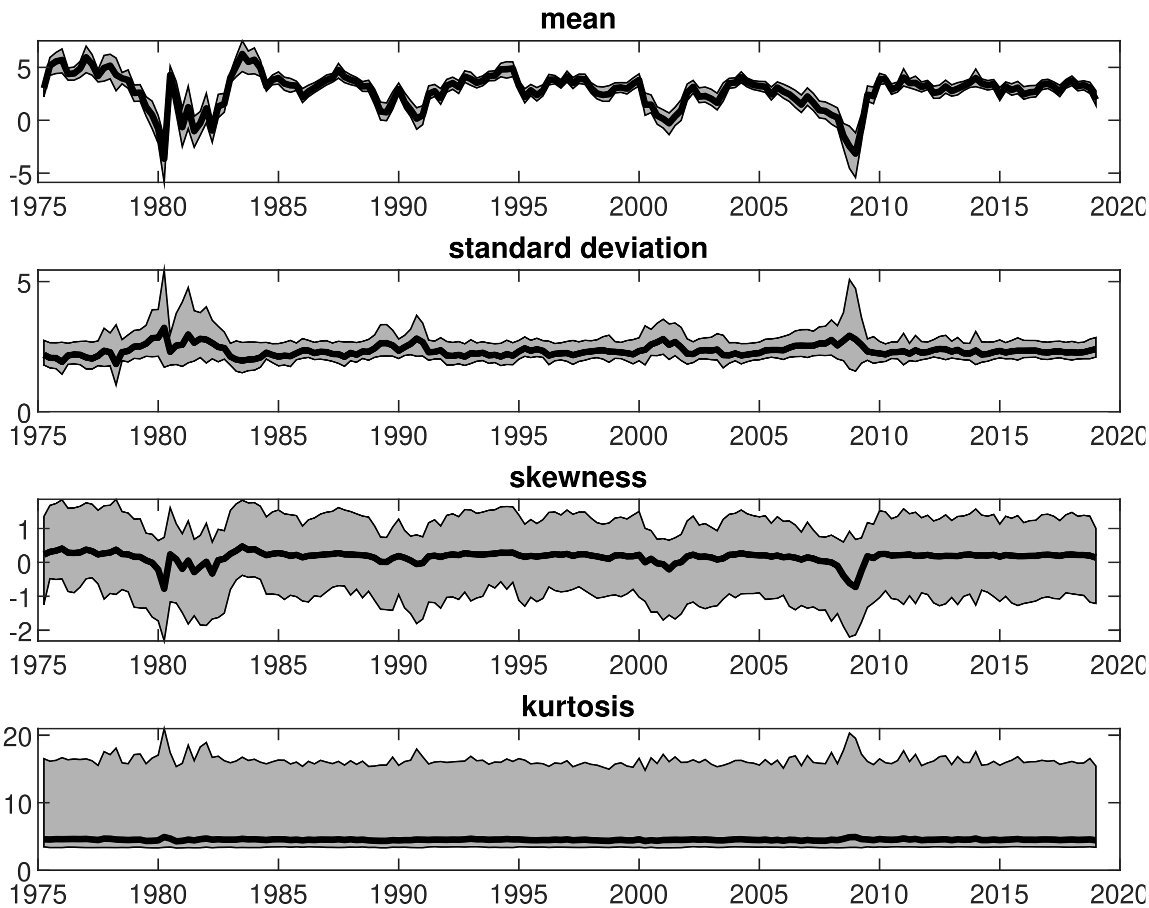
The model and estimation procedure are described in detail in Appendix S.A. As discussed in the appendix, our model can be viewed as a fully Bayesian implementation of the estimation approach developed by Adrian et al. (2019) and used in Section II. An advantage of our approach is that we can easily summarize the posterior uncertainty about time-varying parameters and moments.

III.B. Time-Variation in U.S. Moments and Tail Risk

Figure 10 shows that the data is only able to accurately pin down the time-variation in the *mean* of the one-quarter-ahead conditional distribution of GDP growth. The standard deviation, skewness, and kurtosis of the forecast distribution are much less precisely estimated. The figure shows the posterior median and 90% credible interval for the moments at each point in time. The uncertainty is due to the fact that the underlying model parameters are estimated with varying degrees of precision in the post-1975 data. As is clear from the figure, the implied uncertainty about higher moments is large. Although the posterior median of the conditional standard deviation does fluctuate, quarters with potentially large swings are also associated with high uncertainty. The time paths of skewness and kurtosis are even more imprecisely estimated. Figure S.6 in Appendix S.F shows that all these results are qualitatively unchanged when we look at the conditional moments of the *four*-quarter-ahead forecast distribution.

How does the uncertainty about higher moments affect inferences about the left tail of the growth distribution? The top panel of Figure 11 shows the time-varying implied one-quarter-ahead conditional probability of a recession (i.e., negative growth in

Figure 10: U.S. factor model: Time-varying moments, one quarter ahead.[a]



Sources: FRED-QD, FRED-MD, and authors' calculations.

[a] Time-varying moments of the one-quarter-ahead forecast distribution of GDP growth (annualized). The thick line is the posterior median (across parameter draws) at each point in time. The gray shaded band is the pointwise 90% posterior credible band (across parameter draws) at each point in time. The time axis shows the quarter in which the forecast is made.

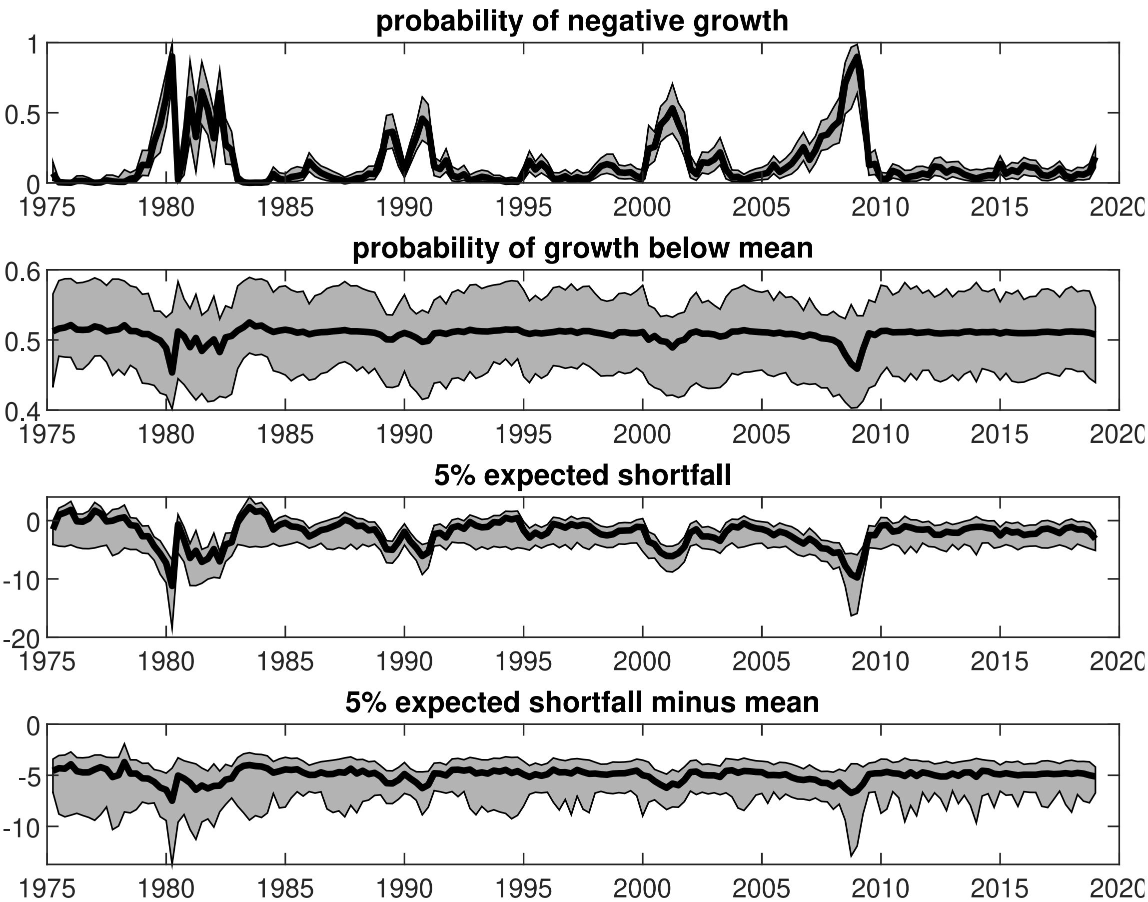
the following quarter). We see that the recession probability varies substantially over time and is reasonably precisely estimated. However, this is purely due to movements in the conditional mean of next-quarter GDP growth, as opposed to movements in the other moments: The second panel of the figure shows the conditional probability of GDP growth falling below the conditional mean; this probability does not vary much over time and is imprecisely estimated. The third panel of the figure shows the *5% expected shortfall*, which is a measure of the severity of a recession, should it materialize (specifically, it equals expected growth conditional on growth falling below the 5th percentile of its conditional distribution). The expected shortfall moves around over time, but the fourth panel – which subtracts off the conditional mean – shows that this movement is almost entirely due to movement in the mean. We report analogous results for four-quarter-ahead forecasts in Appendix S.F; these are qualitatively similar.

Thus, there appears to be little exploitable time-variation in the conditional GDP growth distribution apart from the mean. Although knowing the conditional standard deviation and higher moments would be very helpful for characterizing the risks to GDP growth, it appears that the available data for the U.S. is simply not sufficiently informative about these moments. On the positive side, movements in the conditional mean do appear to be partially predictable, at least in sample. Note that if we are interested in estimating the probability of recessions, and we shut down movement in all moments except for the mean, our model reduces to a probit forecasting model, which is a commonly used specification in applied work.

The financial factor contributes very little to the growth forecasts, whereas the global factor plays a larger role for the conditional mean. Appendix S.F shows the posterior distribution of the model coefficients. The mean coefficients on both factors are statistically significant at conventional levels, but the coefficient on the global factor is estimated to be larger in magnitude. In the appendix we also investigate how the time-varying forecast moments shown in Figure 10 change if we remove the global factor or the financial factor from the conditioning set when producing forecasts. Removing the financial factor has almost no discernible effect on any of the moments, whereas removing the global factor does lead to substantial changes in the path of the conditional mean, especially around the Great Recession period. Thus, as in the out-of-sample results in the previous section, the orthogonal financial factor plays a very minor role in short-term forecasting even *in-sample*.

Figure 10 suggests that the *unconditional* skewness of U.S. GDP growth is indistinguishable from zero, but this result masks a subtle feature of the posterior distribution of the underlying model parameters. In Appendix S.F we show that the marginal posterior distributions for the *intercepts* in the equations for the scale

Figure 11: U.S. factor model: Recession probability and expected shortfall, one quarter ahead.[a]



Sources: FRED-QD, FRED-MD, and authors' calculations.

[a] Recession probability, probability of growth below the conditional mean, expected shortfall, and expected shortfall minus conditional mean for the one-quarter-ahead conditional distribution of GDP growth (annualized). The thick line is the posterior median (across parameter draws) at each point in time. The gray shaded band is the pointwise 90% posterior credible band (across parameter draws) at each point in time. The time axis shows the quarter in which the forecast is made.

parameter σ_t and shape parameter α_t both exhibit a marked bimodality. These two parameters are highly negatively correlated in the posterior. In essence, the data cannot distinguish whether U.S. GDP growth features (i) a low mean but positive skewness, or (ii) a high mean but negative skewness. Notice that this is not a statement about variation in skewness *over time*, but simply a statement about posterior uncertainty about the nature of the unconditional GDP growth distribution. However, we show in Appendix S.F that if the model is estimated on the post-1980 sample, the positive skewness mode disappears. Figure 2 shows that U.S. GDP growth was especially erratic in the late 1970s, and indeed growth from 1975–1979 has a positive sample skewness. Yet the post-1980 data points quite clearly towards negative unconditional skewness. We return to the estimation of unconditional skewness and kurtosis in Section IV.

CROSS-COUNTRY EVIDENCE The fact that time-variation in moments other than the mean is imprecisely estimated holds up in data for other OECD countries. We relegate the discussion of the cross-country data set to the next section, where this data is used more intensively. We estimate a global and financial factor separately for each of 12 other OECD countries, using the same method as we used for the U.S. Appendix S.F shows the estimated time-varying forecast moments for Australia, Italy, and Japan, which are representative of other countries as well. In all cases, the conditional mean of GDP growth is estimated quite precisely, but posterior uncertainty about the model parameters translates into substantial uncertainty about the time paths of the conditional standard deviation, skewness, and kurtosis.

SUMMARY When using lagged GDP growth, a global factor, and a financial factor as predictors, it appears to be highly challenging to accurately estimate the time-variation in the conditional variance, skewness, and kurtosis of GDP growth. The conditional mean, however, is reasonably precisely estimated, and it does appear to vary substantially over time. This is true in data for the U.S. and for other OECD countries. Hence, at least if we ignore out-of-sample forecasting issues, GDP growth forecasting is not a completely futile exercise at short horizons—though all the action is in the mean and none in the tails. More generally, our results demonstrate the importance of taking parameter uncertainty into account when making inferences about rare events from relatively short time series.

However, because we focused on factors as predictors, it remains a possibility that *individual* economic variables might provide strong signals about risks to GDP growth. We turn to this question in the next section.

IV. Which Variables Predict Growth Risk?

Do real activity and financial conditions indices represent the best way to predict and describe growth vulnerability? Policy-makers and academics alike may additionally be interested in which specific economic variables carry most predictive power, for several reasons. First, when designing macro-prudential policies or when explaining such policies to the public, it would be useful to know the most important economic predictor variables, narrowly defined. Second, financial indices – such as the Chicago Fed index used by Adrian et al. (2019) – are usually not constructed to explicitly optimize the ability to forecast *tail risk* in GDP growth. Thus, it is possible that additional predictive power can be gleaned from considering predictor variables individually. Finally, detailed results on the performance of individual predictor variables may shine light on mechanisms that can guide theoretical model-building.

In this section we complement the factor-based analysis of Section III by performing a variable selection exercise to find those specific economic time series that best forecast various moments of GDP growth. We do this by estimating a conditional heteroskedasticity model and the dynamic skew-t model considered in the previous section on U.S. and cross-country data sets, with a wide array of candidate predictor variables. Rather than focusing directly on tail risks, we break down our results by the conditional moments of GDP growth, since this sheds more light on potential mechanisms. Our fully Bayesian approach allows us to describe the uncertainty surrounding the variable selection. For simplicity and clarity, we restrict attention to *one-quarter-ahead* forecasting in this section.

Relative to the literature, our contribution here is to select individual variables – among a large set of candidate variables – that predict GDP growth, its volatility, and higher moments, in data for the U.S. and for 12 other OECD countries. In contrast to the multi-country analyses of Adrian et al. (2018) and Brownlees and Souza (2019), our focus is on variable selection and on characterizing cross-country heterogeneity in growth dynamics. Unlike these papers, we do not explore the role of the forecast horizon.

IV.A. Data

We employ two different data sets: a quarterly U.S. data set and a multi-country data set for 13 OECD countries. In addition to GDP growth (the outcome variable), both data sets contain an extensive set of possible predictor variables. The U.S. data set is especially rich and extends back to 1975, while the predictors in the multi-country data set are slightly more limited in scope and extend back to 1980.

The quarterly U.S. data set is based on the FRED-QD data set constructed by Michael W. McCracken and Serena Ng, building on earlier work by Stock and Watson (2012).[7] This data set is frequently used for high-dimensional prediction in macroeconomics due to its broad scope, reliable data quality, and ease of availability. We select series from various categories of real, price, and financial variables. Though the selected financial series do not cover the full universe used to construct the Chicago Fed's NFCI, we do include corporate spreads; government bond yields; credit and loan volume; federal, corporate, and household balance sheet variables; stock price and dividends; implied volatility; and exchange rates. We supplement with data from Global Financial Data and Haver Analytics on commodity prices; consumer, business, and purchasing manager surveys; and stock trading volume. This yields a total of 43 predictor variables.

The multi-country data set covers 13 OECD countries, with up to 34 predictor variables for each country. As in the U.S. data described above, the potential predictor variables include a variety of real, price, survey, and financial variables. Our overarching goal is to ensure that variable definitions and samples are comparable across countries, so that any cross-country heterogeneity can be interpreted in a straight-forward way. The 13 countries are Australia (AUS), Belgium (BEL), Canada (CAN), Switzerland (CHE), Germany (DEU), Spain (ESP), France (FRA), United Kingdom (GBR), Italy (ITA), Japan (JPN), Netherlands (NLD), Sweden (SWE), and United States (USA).[8] Our primary data source is the OECD Economic Outlook and Main Economic Indicators databases. We supplement with data from the BIS on house prices and credit, financial data from Global Financial Data, and household and business surveys from Haver Analytics.

Exploiting data from several countries could in principle ameliorate the inevitable data limitations when estimating the effect of financial indicators on real growth vulnerability (Adrian et al., 2018). According to Carmen Reinhart's classification,[9] the U.S. has only undergone two banking crises since 1980: the savings and loan crisis in the late 1980s and the global financial crisis of 2007–2010. However, every year from 1980–2014, with the exception of 2002–2006, has witnessed a new or ongoing banking crisis in at least one of the 13 countries in our data set. If we include currency crises in the calculation, only the years 2004 and 2006 were crisis-free in all 13 countries. In an average year, 3.7 countries experience a crisis (standard deviation 2.7). From 1980–2016 there have been a total of 99 country-years of banking crises

[7] `https://research.stlouisfed.org/econ/mccracken/fred-databases/`

[8] Adrian et al. (2018) consider the same countries, excluding Belgium and the Netherlands.

[9] `https://www.hbs.edu/behavioral-finance-and-financial-stability/data/Pages/global.aspx`

and 47 country-years of currency crises for the countries in our data set (just 9 country-years experienced both types of crisis at once).

The full list of all U.S. and multi-country predictor variables (and their abbreviations) can be found in Appendix S.B.

To make coefficients comparable across different predictor variables, we standardize all predictors (but not GDP growth) to have sample mean zero and variance 1, separately for each country.

IV.B. Which Variables Forecast Growth and Its Volatility?

We first attempt to identify important predictors of the *mean* and *volatility* of GDP growth. We will initially restrict attention to a more parsimonious version of the dynamic skew-t model from Section III. Specifically, we assume that only the mean and variance can vary over time, shutting down any potential time-variation in higher moments. This *conditional heteroskedasticity model* was also analyzed by Adrian et al. (2019).

Because we are interested in selecting the relevant predictor variables among a large set of candidates, we employ a Bayesian prior distribution on the model parameters that imposes approximate sparsity, that is, it prefers parsimonious (and thus interpretable) models. Specifically, we impose the “horseshoe prior” of Carvalho et al. (2010), which essentially assumes that the coefficients on the various predictors are either relatively small or relatively large. The practical consequence of imposing this prior is that the posterior distribution will shrink many of the coefficients heavily towards zero, thus yielding a parsimonious model. However, the coefficients on those predictors that are most informative in the data will be shrunk very little. Since we continue to adopt a fully Bayesian approach to inference, it is easy to quantify the uncertainty about the parameters in the model. We give further details about the estimation procedure in Appendix S.A.

RESULTS: U.S. DATA We first estimate the model on the quarterly U.S. data set from 1975q2–2019q2. Lagged GDP growth turns out to not be especially important for either the conditional mean or volatility, conditional on the other predictors variables discussed below. Hence, we report the results for the lagged growth coefficients and the intercepts in Appendix S.G.

Mean forecasting. Which variables help predict the mean of GDP growth? Figure 12 shows the posterior densities for the mean predictor coefficients. Recall that all predictors have been standardized, so that the magnitudes of different coefficients are immediately comparable. About a third of the variables are found to have high posterior probability of being at least somewhat economically important. There is especially high posterior probability of inventories (INVENTO) being an economically important predictor of the mean of GDP growth, with statistically significant roles also played by disposable income (DISPINC), employment (EMPL), new housing permits (HOUSEPERMIT), house prices (HOUSEPRICE), and imports (IMPORT).

The only two financial variables that have a high probability of being important for the mean are implied volatility (VXO) and the spread between AAA corporate bonds and 10-year Treasuries (AAASPR). Perhaps surprisingly, the coefficient on the term spread (TERMSPR) is estimated to be small. There is only weak evidence that credit aggregates may play some role, although business loans (LOANSCORP), business net worth (NWCORP), and household net worth (NWHH) cannot be entirely ruled out.

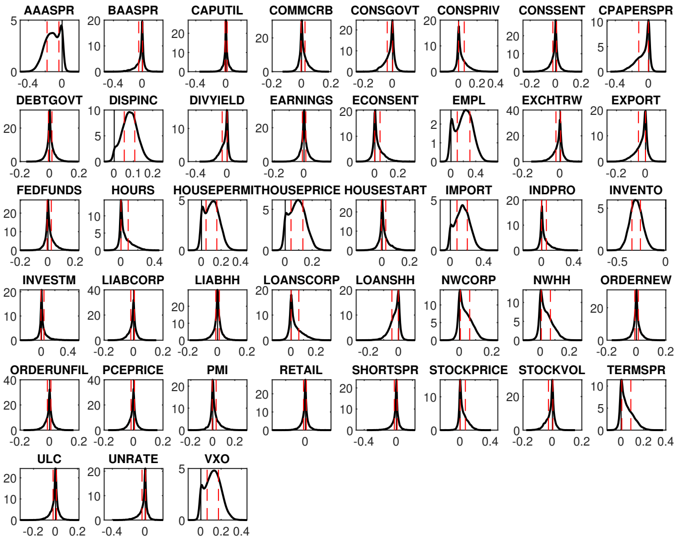
When it comes to volatility forecasting, there is strong evidence of predictive power for only a few variables. Figure 12 shows the posterior densities of the volatility coefficients. The coefficient on the AAA corporate bond spread (AAASPR) has substantial posterior mass at values in the range $[-0.3, -0.1]$ (the posterior median is -0.16), indicating that a *ceteris paribus* one standard deviation increase in this spread is associated with a 10%–30% increase in GDP growth volatility, a potentially substantial effect. Yet the bimodal nature of the posterior density reflects the fact that the data, combined with our prior belief in sparsity, cannot entirely rule out that even this coefficient may be close to 0.

None of the other predictor variables are unambiguously important for volatility forecasting. Other than the AAA spread and lagged GDP growth, no coefficient has a posterior median greater than 0.05 in magnitude. There are five other variables for which the posterior probability of their coefficients exceeding 0.05, or being below -0.05, lies in the range 30–50%: business condition surveys (ECONSENT), housing starts (HOUSESTART), and industrial production (INDPRO) all possibly have a negative association with volatility, while the S&P 500 dividend yield (DIVYIELD) and unit labor cost index (ULC) possibly have a positive association with volatility. Of these variables, the one with the highest degree of posterior certainty is industrial production, for which the posterior probability of lying below -0.05 is a modest 48%.

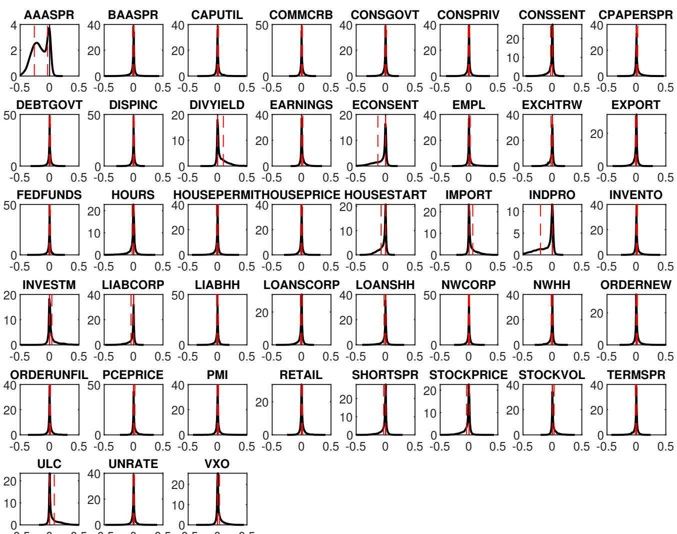
RESULTS: CROSS-COUNTRY DATA Are the predictors of GDP growth and its volatility robustly identifiable across several developed countries? Estimating the conditional heteroskedasticity model separately on 13 OECD countries from 1980q1–2018q4, we find that the answer to this question is a resounding no.

Mean forecasting. Although we found encouraging in-sample results on mean forecasting in U.S. data, the precise identities of the relevant predictor variables

Figure 12: U.S. conditional heteroskedasticity model posterior densities.[a]



Panel (A): Posterior of mean coefficients.



Panel (B): Posterior of volatility coefficients.

Sources: FRED-QD, Global Financial Data, Haver Analytics, and authors' calculations.

[a] Posterior densities of the coefficients on mean and variance predictor variables in the conditional heteroskedasticity model. Vertical red dashed lines indicate posterior interquartile ranges. Panel (A): A coefficient value of 0.1 means that an increase in the predictor by one standard deviation is associated with a 0.1 percentage point increase in the conditional mean of q/q GDP growth. Panel (B): A coefficient value of 0.1 means that an increase in the predictor by one standard deviation is associated with a 10% increase in the conditional volatility of q/q GDP growth.

appear to be highly heterogeneous across the 13 OECD countries. Table 2 shows summary statistics of the posterior distributions of the mean predictor coefficients across countries. Other than lagged GDP growth, only the national stock index (STOCKPRICE) is significant at the 50% level for more than half the countries (in the sense that the posterior interquartile range excludes 0). The coefficients on consumer sentiment (CONSSENT) and the manufacturing production index (MANUF) also have posterior probability greater than 20% (on average across countries) of being larger than 0.1, meaning that a one-standard-deviation increase is associated with 10 basis points higher q/q GDP growth. Other than the stock index, no other financial variables seem important for more than a few countries, including various financial spreads and credit aggregates.

Volatility forecasting. Cross-country heterogeneity is even more pervasive in volatility forecasting. Table 3 shows summary statistics of the posterior distributions of the volatility predictor coefficients across countries. The only volatility predictor variable that is significant at the 50% level for more than 5 countries is the term spread (TERMSPR). Turning to economic significance, it is only the coefficients on S&P 100 implied volatility (VXO, an international variable) and on lagged GDP growth itself (ylag) that have non-negligible posterior probability of being larger than 0.05 in magnitude for more than a handful of countries. Recall that a coefficient magnitude of 0.05 means that a one-standard-deviation change in the variable predicts a 5% change in volatility, a modest amount.

Very few of the posterior medians of the volatility coefficients are economically significant, as shown in Figure 13. The only three variables whose posterior medians are large in magnitude for two or more countries are stock prices (STOCKPRICE), S&P 100 implied volatility (VXO), and the 10-year government bond spread vis-à-vis the U.S. (YIELDSPRUS). However, with the exception of VXO, the signs of the estimated effects of these variables differ across countries. If interest centers on specific countries, however, we do find strong evidence of substantial predictive power for a small number of additional variables, such as economic sentiment surveys (ECONSENT) and the term spread (TERMSPR) for the Netherlands, and house prices (HOUSEPRICE) for Japan.

SUMMARY We arrive at a negative conclusion: Though it is possible to find strong evidence of a few important mean predictors and (less frequently) volatility predictors for individual countries – such as for the U.S. – generalizing to other countries seems fraught with danger. There is little agreement across countries about the identity and sign of important mean and volatility predictors, despite our efforts to construct a data set with comparable variable definitions and data availability.

Table 2: Cross-country conditional heteroskedasticity model: Posterior of mean coefficients.[a]

Variable	#[b]	Average across countries			
		median[c]	signif[d]	P>.1[e]	P<−.1[e]
CA	13	-0.0006	0.08	0.01	0.01
COMMCRB	13	0.0055	0.15	0.03	0.00
CONSGOVT	13	-0.0054	0.08	0.00	0.03
CONSPRIV	13	0.0289	0.23	0.15	0.00
CONSSENT	7	0.0245	0.43	0.17	0.00
CREDCORP	13	0.0019	0.08	0.03	0.02
CREDCORPBNK	13	-0.0052	0.08	0.02	0.04
CREDHH	12	0.0024	0.00	0.04	0.01
DIVYIELD	13	-0.0178	0.31	0.01	0.11
ECONSENT	6	0.0067	0.33	0.06	0.01
EMPL	13	0.0296	0.31	0.15	0.00
EXCHEFF	13	-0.0003	0.00	0.01	0.01
EXCHUSD	12	-0.0081	0.08	0.02	0.05
EXPORT	13	0.0063	0.08	0.05	0.01
GDPDEF	13	0.0010	0.15	0.01	0.01
HOURS	12	0.0126	0.08	0.07	0.00
HOUSEPERMIT	6	0.0261	0.33	0.14	0.00
HOUSEPRICE	13	0.0211	0.46	0.11	0.00
HOUSESTART	8	0.0102	0.13	0.06	0.01
IMPORT	13	0.0155	0.23	0.10	0.00
INTRBNKRATE	13	0.0003	0.00	0.01	0.01
INVESTM	13	0.0227	0.38	0.15	0.03
MANUF	13	0.0497	0.38	0.21	0.00
PMI	1	0.0079	0.00	0.07	0.00
RETAIL	12	0.0011	0.17	0.02	0.02
STOCKPRICE	13	0.0352	0.54	0.20	0.00
STOCKRV	13	-0.0007	0.00	0.01	0.02
STOCKVOL	10	0.0081	0.20	0.06	0.00
TERMSPR	13	0.0072	0.23	0.05	0.01
TERMTRADE	13	0.0032	0.08	0.02	0.01
ULC	12	0.0010	0.25	0.05	0.02
UNRATE	13	-0.0103	0.23	0.00	0.08
VXO	13	0.0015	0.00	0.01	0.01
YIELDSPRUS	12	-0.0039	0.08	0.00	0.03
ylag	13	0.1449	0.77	0.59	0.13

Sources: OECD, BIS, Global Financial Data, Haver Analytics, and authors' calculations.
[a] Summary statistics of the mean coefficient posterior distributions for the 13 OECD countries.
[b] Number of non-missing countries.
[c] Posterior median of coefficient.
[d] Indicator for whether posterior interquartile range for coefficient excludes 0.
[e] Posterior probability that coefficient is > 0.1 or < -0.1, respectively.

Table 3: Cross-country conditional heteroskedasticity model: Posterior of volatility coefficients.[a]

		Average across countries			
Variable	#[b]	median[c]	signif[d]	P>.05[e]	P<−.05[e]
CA	13	-0.0073	0.31	0.06	0.17
COMMCRB	13	-0.0134	0.23	0.07	0.18
CONSGOVT	13	0.0031	0.00	0.11	0.05
CONSPRIV	13	0.0012	0.15	0.13	0.11
CONSSENT	7	-0.0159	0.14	0.04	0.27
CREDCORP	13	-0.0013	0.00	0.07	0.12
CREDCORPBNK	13	-0.0059	0.08	0.06	0.14
CREDHH	12	-0.0012	0.00	0.07	0.12
DIVYIELD	13	0.0018	0.00	0.11	0.05
ECONSENT	6	-0.0745	0.33	0.04	0.32
EMPL	13	-0.0010	0.00	0.08	0.11
EXCHEFF	13	0.0039	0.08	0.11	0.08
EXCHUSD	12	-0.0007	0.00	0.08	0.10
EXPORT	13	-0.0019	0.00	0.05	0.10
GDPDEF	13	-0.0008	0.08	0.07	0.07
HOURS	12	0.0073	0.25	0.13	0.11
HOUSEPERMIT	6	-0.0076	0.17	0.07	0.17
HOUSEPRICE	13	0.0064	0.23	0.11	0.14
HOUSESTART	8	-0.0051	0.25	0.06	0.14
IMPORT	13	0.0079	0.08	0.15	0.05
INTRBNKRATE	13	-0.0014	0.08	0.09	0.09
INVESTM	13	0.0017	0.00	0.09	0.08
MANUF	13	-0.0107	0.15	0.07	0.16
PMI	1	-0.0008	0.00	0.04	0.09
RETAIL	12	-0.0021	0.17	0.10	0.10
STOCKPRICE	13	0.0019	0.23	0.11	0.16
STOCKRV	13	0.0025	0.08	0.13	0.07
STOCKVOL	10	0.0010	0.20	0.11	0.11
TERMSPR	13	-0.0379	0.54	0.04	0.31
TERMTRADE	13	0.0106	0.15	0.14	0.07
ULC	12	0.0057	0.17	0.15	0.05
UNRATE	13	0.0106	0.08	0.15	0.07
VXO	13	0.0596	0.38	0.40	0.01
YIELDSPRUS	12	0.0321	0.42	0.25	0.12
ylag	13	-0.0283	0.38	0.34	0.42

Sources: OECD, BIS, Global Financial Data, Haver Analytics, and authors' calculations.

[a] Summary statistics of the volatility coefficient posterior distributions for the 13 OECD countries.

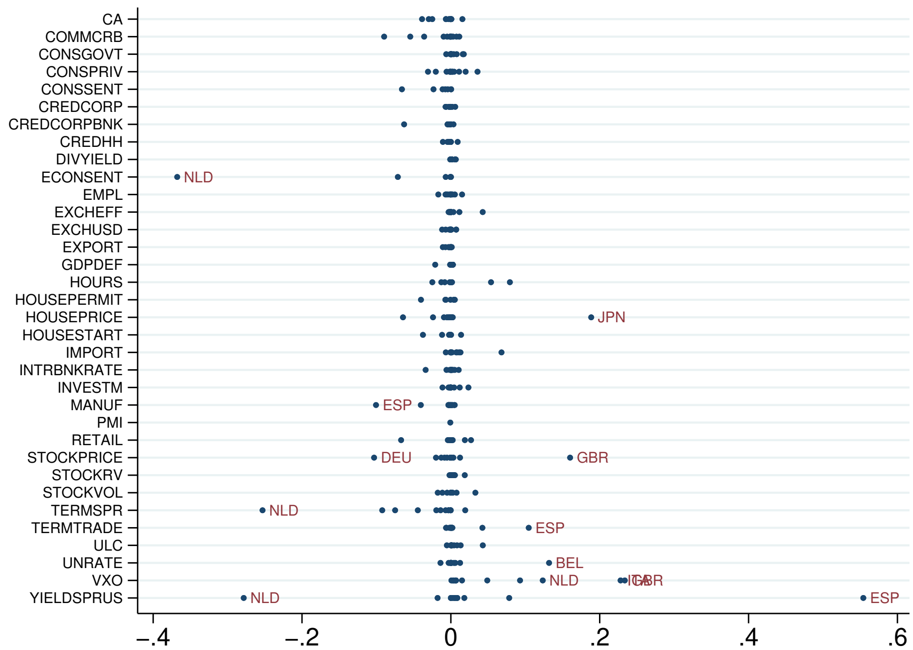
[b] Number of non-missing countries.

[c] Posterior median of coefficient.

[d] Indicator for whether posterior interquartile range for coefficient excludes 0.

[e] Posterior probability that coefficient is > 0.05 or < -0.05, respectively.

Figure 13: Cross-country conditional heteroskedasticity model: Posterior medians of volatility coefficients.[a]



Sources: OECD, BIS, Global Financial Data, Haver Analytics, and authors' calculations.
[a] Posterior medians of the coefficients on volatility predictor variables. Each row in the plot corresponds to a variable, while the dots in each row correspond to different countries.

Contrary to the conjecture mentioned in Section I that financial spreads and credit aggregates might carry different information about growth vulnerability, we do not find a robust role for either type of variable in mean or volatility forecasting. No financial variable in our data set plays a statistically and economically significant role in forecasting GDP growth at short horizons for more than a handful of the 13 countries we consider. We stress, though, that our cross-country data set does not contain a measure of corporate borrowing spreads due to data availability. Thus, our analysis does not overturn the existing literature discussed in the introduction, although it does caution against putting too much faith in single-country analyses.

IV.C. Which Variables Are Informative About Higher Moments?

Can we go beyond the mean or volatility and characterize the predictors of time-variation in the skewness of GDP growth? To answer this question, we turn again to the full dynamic skew-t model described in Section III, but instead of using a small number of factors as explanatory variables, we use our full set of individual economic predictor variables.[10]

In short, we find little robust evidence of individual predictors being informative about the *time-variation* of skewness. In Appendix S.G we define a measure of the skewness of the forecast distribution with interpretable units, called "TVD". This measure lies between 0 and 1, with 1 indicating substantial skewness and 0 indicating a symmetric distribution. Using this measure, we find that no predictor variable has an economically significant positive or negative effect on the time-variation of skewness in more than a few of the countries in our analysis. The results are relegated to the appendix due to space constraints.

The distribution of GDP growth does exhibit clear *unconditional* skewness as well as moderate kurtosis in many countries. Table 4 displays, for each country, posterior summaries of α_t, $TVD(\alpha_t)$, and ν (Japan and Spain have been dropped from the analysis due to numerical convergence issues for these countries). Based on time-averaged TVD, most countries exhibit substantial skewness, as values of TVD around 25–40% indicate substantial departures from symmetry. From the time-averaged α_t values it is clear, however, that the direction of skewness varies across countries: GDP growth tends to be negatively skewed in Switzerland, Germany, France, Netherlands, and U.S., and positively skewed in the other countries. As expected based on the above results, there does not appear to be substantial time-variation in the extent of the skew, as can be seen by comparing the average and standard deviation of TVD over time within countries.[11] As for kurtosis, all countries but the United Kingdom have posterior medians of ν in excess of 10, indicating at most moderately fat tails.

SUMMARY Skewness – and to a lesser extent fat tails – do seem to be pervasive features of the unconditional GDP growth distribution in many countries, but attributing the time-variation in these higher moments to specific interpretable economic variables appears challenging given available data. This echoes the result in Section III, which used aggregated factors as predictor variables. In particular, corporate or household credit growth is not robustly associated with negative conditional skewness of GDP growth. Adrian et al. (2018) find evidence for an interaction effect in cross-country data: When credit growth is high, financial conditions are stronger predictors of risks to GDP growth at short horizons. Although we do not have explicit interaction terms in our model, the dynamic skew-t model can in princi-

[10]It turns out to be computationally difficult to impose a prior belief in sparsity in the full dynamic skew-t model, unlike in the conditional heteroskedasticity model considered in Section IV.B. Hence, we here instead use conventional normal shrinkage priors. See Appendix S.A for details.

[11]This is consistent with the conclusion of Adrian et al. (2019, p. 1276), who however do not report measures of parameter uncertainty.

Table 4: Cross-country skew-t model: Unconditional skewness and kurtosis.[a]

Country	avg(α)[b]	avg(TVD)[c]	std(TVD)[c]	Q1(ν)[d]	med(ν)[d]	Q3(ν)[d]
AUS	5.224	0.387	0.087	12.0	18.0	26.7
BEL	1.747	0.311	0.092	7.6	13.0	21.6
CAN	0.472	0.273	0.101	12.0	18.3	27.4
CHE	-0.821	0.243	0.081	8.5	13.0	20.2
DEU	-5.574	0.363	0.093	13.5	20.1	29.4
FRA	-0.160	0.248	0.100	12.0	18.2	26.9
GBR	1.578	0.307	0.107	4.5	7.1	12.5
ITA	4.229	0.369	0.089	12.8	19.4	28.5
NLD	-4.719	0.392	0.087	10.9	16.7	25.4
SWE	2.381	0.331	0.114	6.5	10.0	16.2
USA	-2.194	0.321	0.096	14.6	21.5	31.0

Sources: OECD, BIS, Global Financial Data, Haver Analytics, and authors' calculations.
[a] Unconditional higher moments of the GDP growth distribution, for 11 OECD countries.
[b] Posterior mean of average (across time) of α_t.
[c] Posterior means of average and standard deviation (across time) of $TVD(\alpha_t)$, respectively.
[d] Posterior first quartile, median, and third quartile of ν, respectively.

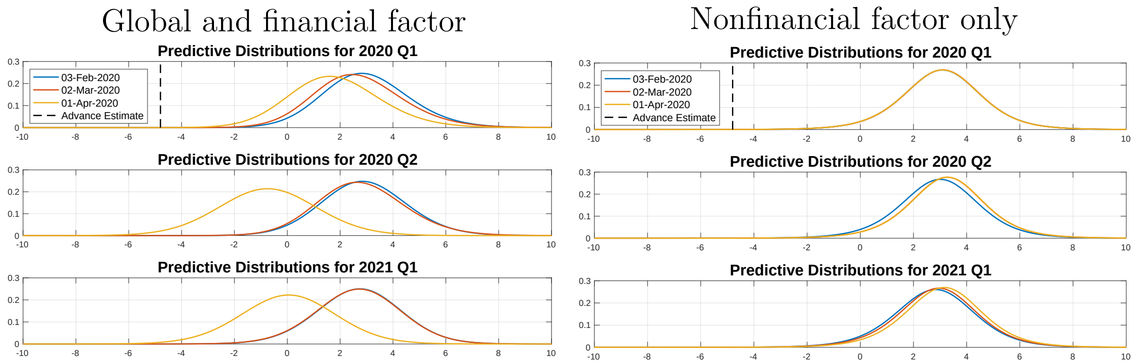
ple generate this empirical pattern if credit growth negatively affects skewness while other financial variables affect the mean and/or variance of GDP growth. However, we do not find evidence for this mechanism in our data set. It is an interesting topic for future research to extend the dynamic skew-t model to allow for further state dependence.

V. Case Study: COVID-19

COVID-19 struck the world economy unexpected. A sharp recession in the U.S., as in other parts of the world, was induced by the lock-down of a large part of the economy. Given the typical delay of macroeconomic information, it has been very difficult for traditional nowcasting and forecasting models to obtain meaningful numbers for the evolution of GDP in the first and second quarter of 2020. The most recent published figure for first quarter growth is -4.8%, well below expectations. This provides a natural experiment for the analysis of this paper. Would the nowcast in real time have been more accurate in models that include financial variables?

Using the same nonparametric real-time estimation approach as in Section II, we compute here the predictive distribution of GDP for the first and second quarter

Figure 14: Predictive distributions of GDP growth in the COVID-19 crisis.[a]



Sources: Bureau of Economic Analysis (BEA) and authors' calculations.

[a] Quarter-by-quarter evolution of the predictive distributions for the COVID-19 crisis, for the models including (i) the global factor and the financial factor (left panel), (ii) the nonfinancial factor (right panel). The chart for 2020Q1 reports also the BEA advance estimate of annualized GDP growth.

of 2020 and the first quarter of 2021. We condition on information available at three different dates: the first business days of February, March, and April 2020. It is important to notice that – apart from financial variables – no common business cycle indicators relating to the lockdown period were available until the end of April. However, news stories and policy discussion of the virus were rampant starting in January 2020, and this information could potentially have been reflected in asset prices, business and consumer surveys, and so on. We consider two models. The first includes the macro-financial common factor (global factor) and the orthogonal financial factor (results are shown in Panel A of Figure 14). The second model conditions on the non-financial factor only (Panel B of the same figure).

Figure 14 shows that financial variables do provide useful timely information about the COVID-19 downturn, although they react relatively late and severely undershoot the magnitude. The forecast distributions of GDP growth for 2020Q1, 2020Q2, and 2021Q1 hardly move at all if we condition only on lagged GDP growth and the non-financial factor, even though in reality the economy contracted markedly in March. However, when conditioning on the global and financial factors, the predictive distributions for the first two quarters of 2020 and for one year ahead start moving to the left in the beginning of April. According to our data release calendar, and given the *ad hoc* convention that financial variables for March are released on April 1st, at that date the only information available concerning March was financial data. At that time, surveys and macro variables were only available for January and

February, before the lock-down went into effect. Thus, financial variables proved to be useful for nowcasting this particular episode. Notice, however, that none of the forecasts came close to predicting the actual scale of the downturn. Moreover, financial variables only started flashing warning signs in late February, mere days before dramatic policy actions were introduced in several U.S. states.

Why did financial variables not similarly provide a timely warning in the early stages of the 2008–09 recession, as discussed in Section II? The difference is that when in January 2009 the model updated the estimate for 2008Q4, it could exploit information from both macro and financial data for October and November. These data points already signaled a fall in output. Hence, in this case the information from financial variables about December 2008 just served to confirm the negative signal, without providing truly novel information, unlike in the COVID-19 episode.

In summary, this small COVID-19 case study suggests that financial variables can sometimes be useful timely indicators at short horizons when no other information is available from macroeconomic surveys and the like. Moreover, while financial variables correctly hinted at a directional movement in the GDP growth distribution, the actual forecast was still very poor relative to the realization. Thus, the conclusion of our analysis of the uncertainty surrounding forecasts of moments other than the mean, which we have provided in the previous sections, remains in force: One should not place too much confidence in the signaling ability of financial variables.

VI. Summary and Conclusions

The results presented in this paper indicate that financial variables have very limited predictive power for the distribution of GDP growth at short horizons, especially – but not limited to – the tail risk. Two factors drive these results.

First, moments other than the mean are estimated very imprecisely. Although our findings confirm that GDP growth in many countries exhibits a skewed unconditional distribution, it is very hard to precisely estimate the dynamics over time of variance, skewness and kurtosis conditional on financial and macroeconomic variables. This implies that, when computing the probability of recessions from the estimated moments, we essentially obtain what we could have obtained by using a probit model. These results are true whether we allow individual variables to enter the model in a flexible way via a variable selection algorithm or we aggregate them as factors. The variable selection exercise does not point to any stable stylized facts, except for the finding that real indicators are selected more often than financial ones. While our results do not rule out a transmission of shocks from the level of variables to their variance and other moments, as sometimes postulated in stochastic volatility models, this mechanism is empirically tenuous.

Second, information in monthly financial variables is highly correlated with information in macroecomic variables, especially in recessions, but the correlation is contemporaneous. As the economy enters a recession and we observe a fall in output, markets have a sudden change in sentiments which leads to a spike in the spread variables. A common factor extracted from financial and macro data usually predicts a fall in the mean of GDP during the onset of the recession, but no further predictive power is gained by adding an extra orthogonal factor capturing financial-specific information.

In our real-time nowcasting exercise, which takes into account data uncertainty and the release calendar of economic data, we showed that the timeliness advantage of financial variables is generally miniscule. The case study of the COVID-19 lockdown episode, however, shows that financial variables can in some unique instances provide early warning signs when other macroeconomic data is not yet available. Still, even in this episode, models with financial data missed the severity of the downturn. Thus, the timeliness of financial information may help in real time, but should not be over-interpreted, and financial markets do not seem to contain much *forward-looking* information about the macroeconomy beyond the current quarter.

The substantial cross-country heterogeneity in the identities of important predictor variables calls for humility in theoretical model-building: The precise channels of the financial-real vulnerability nexus are difficult to tease out from the available data. In particular, it is likely a mistake to treat broad financial conditions indices as catch-all representations of any arbitrary financial friction that is of theoretical interest. Lack of predictive power might be the result of time instability between financial variables and GDP, which in turn may caused by changes to the financial system and the conduct of monetary policy. This is something to be investigated further in future research.

Future research may also investigate whether our methods overlook state dependency and interactions between financial fragility and macroeconomic dynamics. For example, Krishnamurthy and Muir (2017) find that the interaction between credit spreads and pre-crisis credit growth can forecast the severity of the crisis. Aikman et al. (2016) find that, when private non-financial leverage is above trend, an easing of financial conditions predicts an economic expansion in the near term and a contraction in the following quarters. This is an interesting line of research which has implication for policy, as emphasized by Adrian et al. (2018). It implies that, although recessions are fundamentally unpredictable, prudential action can make the system less fragile so that, when they occur, the damage is limited. Although we do not directly investigate the role of such interactions, our results at the very least suggest that empirical analysis of this phenomenon must be fraught with substantial estimation uncertainty.

References

Adrian, T., N. Boyarchenko, and D. Giannone (2019): "Vulnerable Growth," *American Economic Review*, 109, 1263–1289.

Adrian, T., F. Grinberg, N. Liang, and S. Malik (2018): "The Term Structure of Growth-at-Risk," IMF Working Paper No. 18/180.

Aikman, D., A. Lehnert, J. N. Liang, and M. Modugno (2016): "Financial Vulnerabilities, Macroeconomic Dynamics, and Monetary Policy," Finance and Economics Discussion Series 2016-055, Board of Governors of the Federal Reserve System (U.S.).

Azzalini, A. and A. Capitanio (2003): "Distributions Generated by Perturbation of Symmetry with Emphasis on a Multivariate Skew t-Distribution," *Journal of the Royal Statistical Society. Series B (Statistical Methodology)*, 65, 367–389.

Basel Committee for Banking Supervision (2010): *Guidance for national authorities operating the countercyclical capital buffer*, Bank for International Settlements.

Bernanke, B. (2018): "The Real Effects of the Financial Crisis," Tech. rep., BPEA Conference Draft, Fall.

Bernanke, B. and M. Gertler (1989): "Agency Costs, Net Worth, and Business Fluctuations," *American Economic Review*, 79, 14–31.

Bernanke, B. S., M. Gertler, and S. Gilchrist (1999): "The financial accelerator in a quantitative business cycle framework," in *Handbook of Macroeconomics*, ed. by J. B. Taylor and M. Woodford, Elsevier, vol. 1 of *Handbook of Macroeconomics*, chap. 21, 1341–1393.

Bloom, N. (2014): "Fluctuations in Uncertainty," *Journal of Economic Perspectives*, 28, 153–176.

Bloom, N., F. Guvenen, and S. Salgado (2016): "Skewed Business Cycles," 2016 Meeting Papers 1621, Society for Economic Dynamics.

Borio, C. and P. Lowe (2002): "Asset prices, financial and monetary stability: exploring the nexus," BIS Working Papers 114, Bank for International Settlements.

Boyarchenko, N., T. Adrian, and D. Giannone (2019): "Multimodality in Macro-Financial Dynamics," Staff Reports 903, Federal Reserve Bank of New York.

Brave, S. and A. Butters (2012): "Diagnosing the Financial System: Financial Conditions and Financial Stress," *International Journal of Central Banking*, 8, 191–239.

Brownlees, C. and A. B. Souza (2019): "Backtesting Global Growth-at-Risk," Manuscript, Universitat Pompeo Fabra.

Brunnermeier, M. K., D. Palia, K. A. Sastry, and C. A. Sims (2019): "Feedbacks: Financial Markets and Economic Activity," Working Papers 257, Princeton University, Department of Economics, Center for Economic Policy Studies.

Carvalho, C. M., N. G. Polson, and J. G. Scott (2010): "The horseshoe estimator for sparse signals," *Biometrika*, 97, 465–480.

Claessens, S., M. A. Kose, and M. E. Terrones (2012): "How do business and financial cycles interact?" *Journal of International Economics*, 87, 178–190.

Delle Monache, D., A. D. Polis, and I. Petrella (2019): "Modeling and Forecasting Macroeconomic Downside Risk," Mimeo.

Doz, C., D. Giannone, and L. Reichlin (2012): "A Quasi-Maximum Likelihood Approach for Large, Approximate Dynamic Factor Models," *The Review of Economics and Statistics*, 94, 1014–1024.

Drehmann, M., C. Borio, and K. Tsatsaronis (2012): "Characterising the financial cycle: don't lose sight of the medium term!" BIS Working Papers 380, Bank for International Settlements.

Fagiolo, G., M. Napoletano, and A. Roventini (2008): "Are output growth-rate distributions fat-tailed? some evidence from OECD countries," *Journal of Applied Econometrics*, 23, 639–669.

Figueres, J. M. and M. Jarociński (2019): "Vulnerable Growth in the Euro Area: Measuring the Financial Conditions," Manuscript.

Forni, M., M. Hallin, M. Lippi, and L. Reichlin (2003): "Do financial variables help forecasting inflation and real activity in the euro area?" *Journal of Monetary Economics*, 50, 1243–1255.

Gertler, M. and S. Gilchrist (2018): "What Happened: Financial Factors in the Great Recession," *Journal of Economic Perspectives*, 32, 3–30.

Giannone, D., M. Lenza, and L. Reichlin (2019): "Money, Credit, Monetary Policy, and the Business Cycle in the Euro Area: What Has Changed Since the Crisis?" *International Journal of Central Banking*, 15, 137–173.

Giannone, D., L. Reichlin, and D. Small (2008): "Nowcasting: The real-time informational content of macroeconomic data," *Journal of Monetary Economics*, 55, 665–676.

Giglio, S., B. Kelly, and S. Pruitt (2016): "Systemic risk and the macroeconomy: An empirical evaluation," *Journal of Financial Economics*, 119, 457 – 471.

Gilchrist, S. and E. Zakrajšek (2012): "Credit Spreads and Business Cycle Fluctuations," *American Economic Review*, 102, 1692–1720.

Hatzius, J., P. Hooper, F. S. Mishkin, K. L. Schoenholtz, and M. W. Watson (2010): "Financial Conditions Indexes: A Fresh Look after the Financial Crisis," NBER Working Papers 16150, National Bureau of Economic Research, Inc.

Jorda, O., S. Moritz, and A. M. Taylor (2011): "Financial Crises, Credit Booms, and External Imbalances: 140 Years of Lessons," *IMF Economic Review*, 59(2), 340–378.

Jorda, O., M. Schularick, and A. M. Taylor (2013): "When Credit Bites Back," *Journal of Money, Credit and Banking*, 45, 3–28.

Kiley, M. T. (2018): "Unemployment Risk," Finance and Economics Discussion Series 2018-067, Board of Governors of the Federal Reserve System (U.S.).

Kilian, L. and S. Manganelli (2008): "The Central Banker as a Risk Manager: Estimating the Federal Reserve's Preferences under Greenspan," *Journal of Money, Credit and Banking*, 40, 1103–1129.

Kiyotaki, N. and J. Moore (1997): "Credit Cycles," *Journal of Political Economy*, 105, 211–248.

Krishnamurthy, A. and T. Muir (2017): "How Credit Cycles across a Financial Crisis," NBER Working Papers 23850, National Bureau of Economic Research.

Laeven, L. and F. Valencia (2012): “Systemic Banking Crises Database: An Update,” IMF Working Paper 12/163, International Monetary Fund.

Loria, F., C. Matthes, and D. Zhang (2019): “Assessing Macroeconomic Tail Risk,” Working Paper 19-10, Federal Reserve Bank of Richmond.

McCracken, M. W. and S. Ng (2016): “FRED-MD: A Monthly Database for Macroeconomic Research,” *Journal of Business & Economic Statistics*, 34, 574–589.

Prasad, A., S. Elekdag, P. Jeasakul, R. Lafarguette, A. Alter, A. X. Feng, and C. Wang (2019): “Growth at Risk: Concept and Application in IMF Country Surveillance,” Working Paper Series 19/36, International Monetary Fund.

Reichlin, L., G. Ricco, and T. Hasenzagl (2020): “Financial Variables as Predictors of Real Growth Vulnerability,” CEPR Discussion Papers 14322, C.E.P.R. Discussion Papers.

Reinhart, C. M. and K. S. Rogoff (2009): “The Aftermath of Financial Crises,” *American Economic Review*, 99, 466–72.

Schularick, M. and A. M. Taylor (2012): “Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008,” *American Economic Review*, 102, 1029–61.

Stock, J. H. and M. W. Watson (2003): “Forecasting Output and Inflation: The Role of Asset Prices,” *Journal of Economic Literature*, 41, 788–829.

——— (2012): “Disentangling the Channels of the 2007–09 Recession,” *Brookings Papers on Economic Activity*, Spring 2012, 81–135.