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When Is Growth at Risk?

ABSTRACT This paper empirically evaluates the potentially nonlinear nexus between financial indicators and the distribution of future GDP growth, using a rich set of macroeconomic and financial variables covering thirteen 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 nonparametric 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.

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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 involves not only 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, Gertler, and Gilchrist (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 of 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 policymakers 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 (Gertler and Gilchrist 2018). 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 United States, 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 Bank for International Settlements (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 (Basel Committee for Banking Supervision 2010). Some studies have pointed at a correlation of excess growth in leverage and financial crises (Jordà, Schularick, and Taylor 2011, 2013; Schularick and Taylor 2012) and found that recessions preceded by financial crises are deeper and followed by slower recoveries (Reinhart and Rogoff 2009; Valencia and Laeven 2012).[1] However, this literature is mainly concerned with long-term features of the nexus between finance and the macroeconomy and on financial crises rather than recessions. At business cycle frequency, growth rates of credit aggregates are found to be procyclical and lagging (Giannone, Lenza, and Reichlin 2019). In a recent paper, Brunnermeier and others (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 (Stock and Watson 2003; Forni and others 2003; Hatzius and others 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 nonlinear 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 nonlinearly has recently inspired a line of research which uses nonparametric methods in order to study the predictive distribution of GDP and its evolution in relation to financial conditions. Giglio, Kelly, and Pruitt (2016) and Adrian, Boyarchenko, and Giannone (2019a) 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 United States, such an index is constructed by the Federal Reserve Bank of Chicago—the National Financial Conditions

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 (Borio and Lowe 2002; Drehmann, Borio, and Tsatsaronis 2012; Claessens, Kose, and Terrones 2012).

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 nonlinear relationship between financial and real variables. New research is building on these ideas. Recent contributions are by Kiley (2018), Adrian, Boyarchenko, and Giannone (2019b), Loria, Matthes, and Zhang (2019), Brownlees and Souza (2019), and Figueres and Jarociński (2020).

As proposed by Adrian and others (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.[2] The appeal of this approach to policy work, in particular macroprudential, is that it provides a framework in which forecasting can be thought of as a risk-managing exercise.[3]

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, Ricco, and Hasenzagl (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 nonparametric approach of Adrian, Boyarchenko, and Giannone (2019a), 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.

2. See, for example, Prasad and others (2019) for a description of the use of this method at the IMF.

3. See Greenspan (2004) and Kilian and Manganelli (2008).

Second, we want to evaluate whether nonlinearities 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 macroprudential policy. The out-of-sample evaluation takes into 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 nonparametric method proposed by Giglio, Kelly, and Pruitt (2016) and Adrian, Boyarchenko, and Giannone (2019a), while for the second purpose we use a fully parametric implementation of their approach. The motivation for using two different models is that the nonparametric approach very flexibly captures nonlinearities 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, Ricco, and Hazenzagl (2020)—financial variables have very different dynamic properties so that, by aggregating predictors into financial and real indexes 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 policymakers and academics to hone in on specific mechanisms of growth fragility. We consider both US data and a panel of twelve other Organisation for Economic Cooperation and Development (OECD) countries. This allows us to consider more than a few recessionary events in our sample. For the United States, for which we have a richer data set, we perform the analysis both separately and in combination with other countries' data.

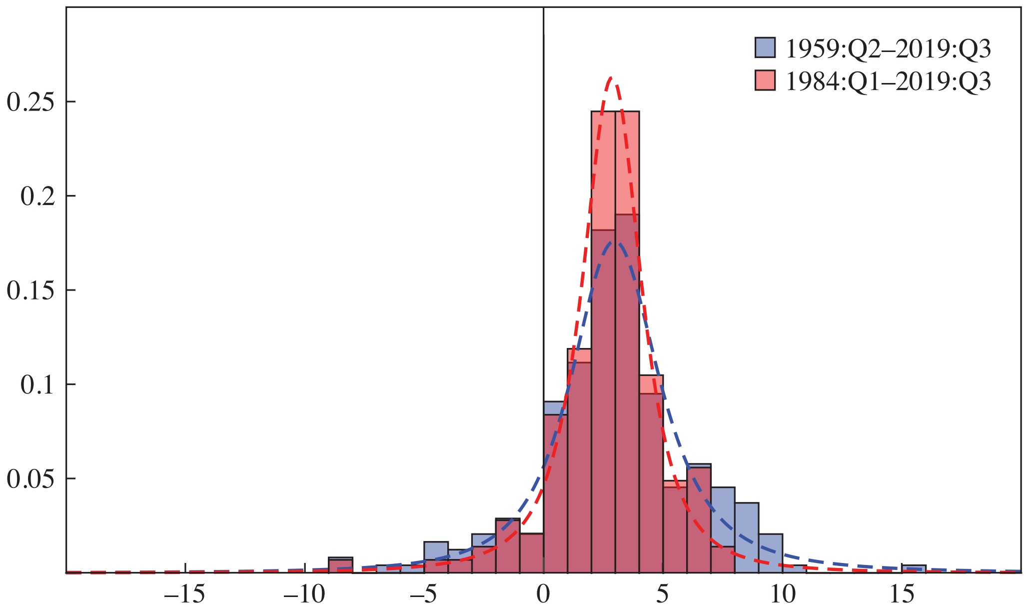
The overall conclusion of our analysis is pessimistic on the ability of the data to tell us something more than the evolution of the conditional mean. All other time-varying moments are imprecisely estimated. Moreover, both the out-of-sample analysis and the in-sample results point to very little additional 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 relative to other data, since survey data are almost as timely and highly correlated with macroeconomic data. Finally, when single variables are allowed to enter into the model flexibly, 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 section V, we run the real-time experiment over the recent COVID-19 lockdown 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 nonfinancial 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 nonlinearities 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 macroprudential 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 sections of the paper are 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

Figure 1. Annual Real GDP Growth



Sources: FRED-QD and authors' calculations.

Notes: Histograms of annual real GDP growth over the samples 1959:Q2–2019:Q3 and 1984:Q1–2019:Q3. The fitted distributions are computed by adopting the flexible skew *t*-distribution developed by Azzalini and Capitanio (2003).

orthogonal to the global factor. Section IV abandons the factor-based predictors and instead asks whether there are any specific individual economic 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 lockdown episode in section V. Section VI concludes.

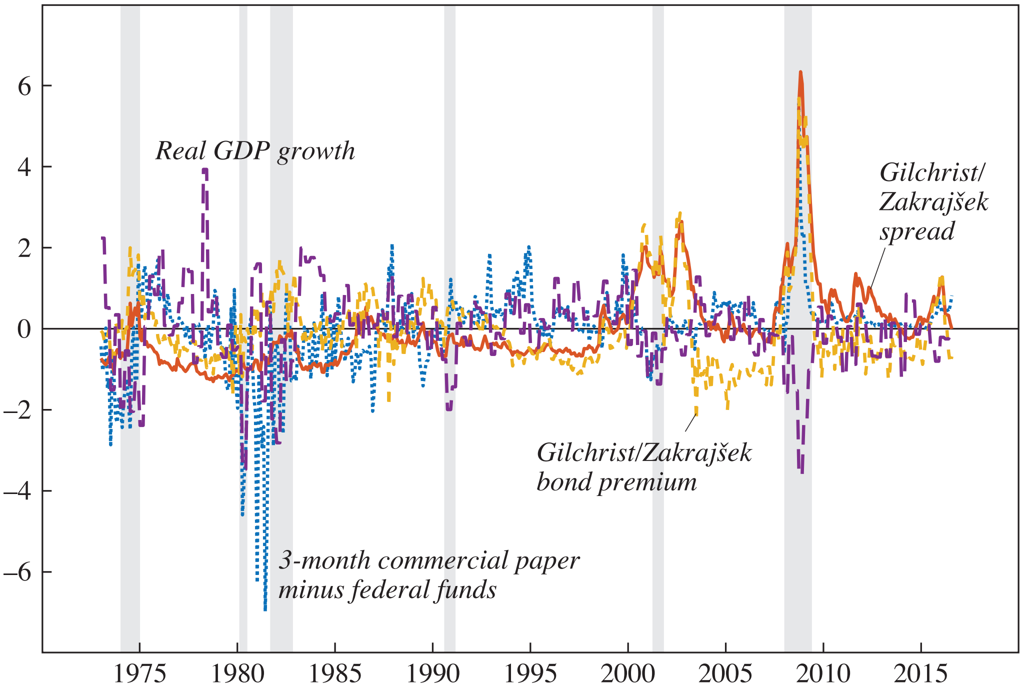
I. A Few Motivational Facts

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

I.A. Fact 1: Economic Fluctuations Are Asymmetric over the Business Cycle

Figure 1 shows that the distribution of US GDP growth exhibits some skewness and fat tails. The figure plots the histograms of annual real GDP growth over the samples 1959:Q2–2019:Q3 and 1984:Q1–2019:Q3 and the associated fitted distributions. The dark area marks 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

Figure 2. Financial Stress Indicators and GDP Growth Rates



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

(mean) shock and a positive second-moment (uncertainty) shock (Bloom 2014) or as negative third-moment (skewness) shocks (Bloom, Guvenen, and Salgado 2019), and fat tails have been found to be a feature of GDP distribution in many advanced economies (Fagiolo, Napoletano, and Roventini 2008).

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

I.B. 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 1973:Q1 to 2016:Q3 against three credit spreads that have been considered in the literature as measures of financial risk (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 moments of the GDP conditional distribution. As discussed above, this idea has been the inspiration for the literature that has explored the predictive power of financial variables for moments other than the mean, which we seek to evaluate in this paper.

I.C. Fact 3: Movements in Financial Conditions 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 NFCI and of a business cycle index computed from a large set of monthly macroeconomic indicators.[4]

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

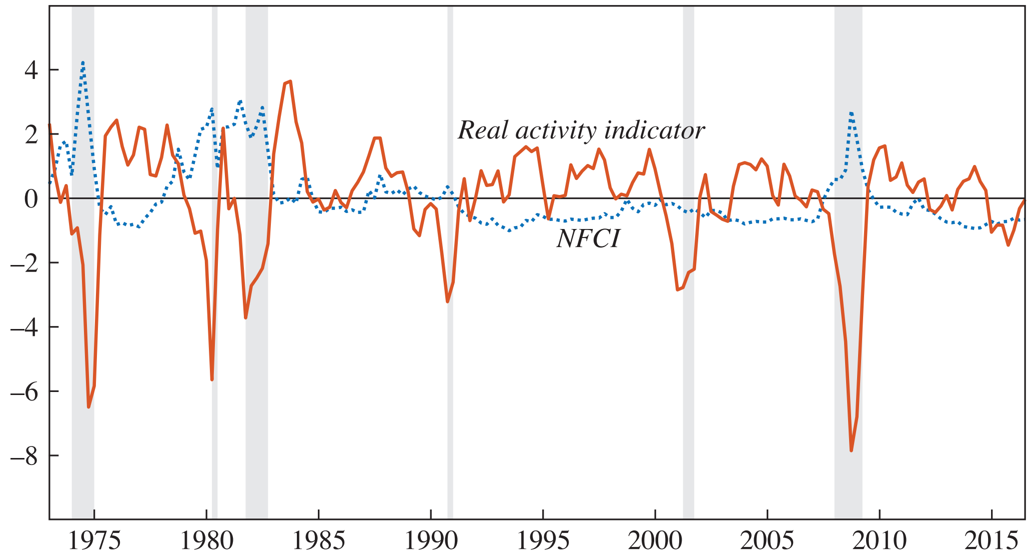
This fact suggests that, in order to establish the role of financial variables for predicting the GDP distribution, one should control for the common and contemporaneous component (what we define as the "global factor") and focus on the additional "marginal" information available in the financial indicators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

I.D. Fact 4: Different Types of Financial Variables Have Heterogeneous 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

4. The business cycle index is computed as the first common factor to all of the variables in the FRED-MD data set, except the ones classified as financial. Online appendixes S.A and S.B provide details on the estimation of the factor. 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, nonfinancial, 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 Federal Reserve Bank of Chicago's dedicated website: https://www.chicagofed.org/publications/nfci/index. Both factors are estimated by maximum likelihood following Doz, Giannone, and Reichlin (2012) and averaged across quarters. Table S.4 in the online appendix S.D reports the full set of estimated values for the model coefficients.

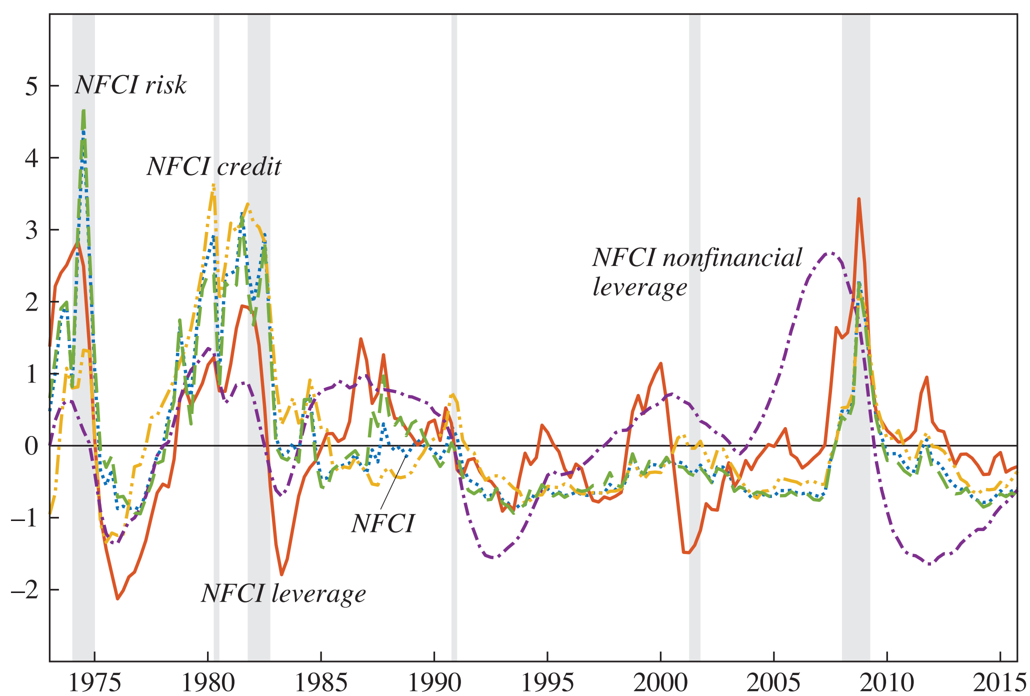
Figure 3. Business Cycle and Financial Condition Indexes



Source: Authors' calculations.

Note: 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 NFCI. The time sample is 1973:Q1–2016:Q3.

Figure 4. Heterogeneous Dynamics of Financial Indicators



Source: FRED-QD.

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 nonfinancial 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.[5]

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—forecasting one quarter 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.

5. See Bernanke (2018) for an analysis of the 2008 recession in the United States.

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

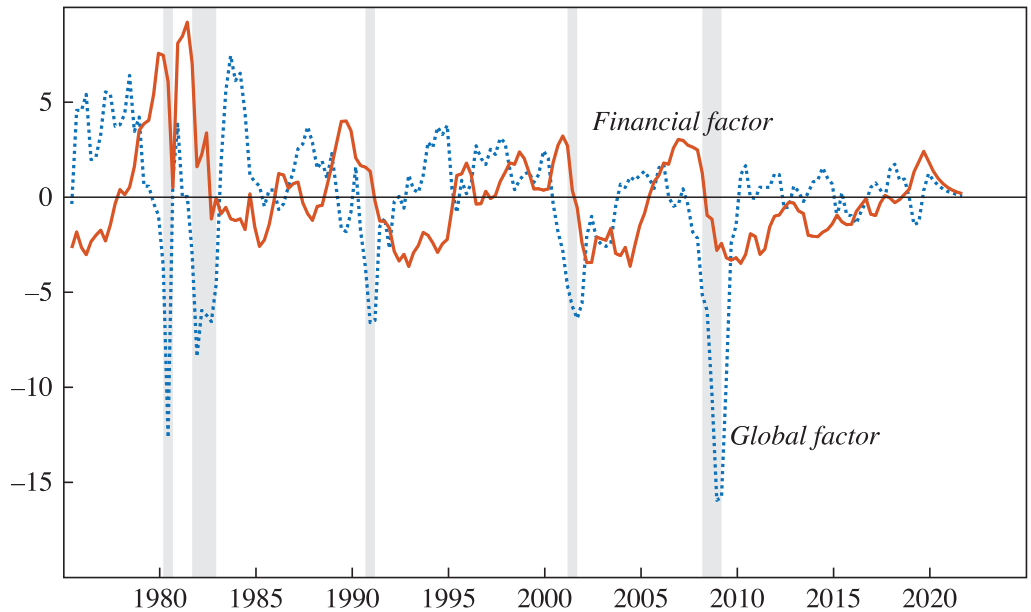
We first ask the following questions: How do the moments of the predictive distribution vary over time? Do financial variables capture shifts in the predictive mean, variance, or higher moments of the GDP distribution? Is it possible to predict an increase in GDP growth vulnerability out of sample? This 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 from the data uncertainty that characterizes data 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 indexes 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) Federal Reserve Economic Data Monthly Database (FRED-MD) data set, 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. Online appendix S.A provides details on the factor models adopted to estimate the factors.[6] Table S.1 in online appendix S.B provides details on the data set and on the assumptions adopted to estimate the factors.

The key difference from the analysis of Adrian, Boyarchenko, and Giannone (2019a) 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, Ricco, and Hasenzagl (2020) observe that the NFCI is largely endogenous to economic conditions in the United States and that it has high correlation with a factor extracted from nonfinancial 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.

6. Figure S.1 in online appendix S.C reports the estimated loadings for the factor model with a global factor and a financial factor.

Figure 5. Global and Financial Factors



Source: Authors' calculations.
Note: The time sample is 1975:Q2–2021:Q3. The values between 1975:Q2 and 2019:Q3 are in-sample estimates of the factors and the values between 2019:Q4 and 2021:Q3 are out-of-sample forecasts.

We employ the factors as predictors in the nonparametric quantile regression framework of Adrian, Boyarchenko, and Giannone (2019a). 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,

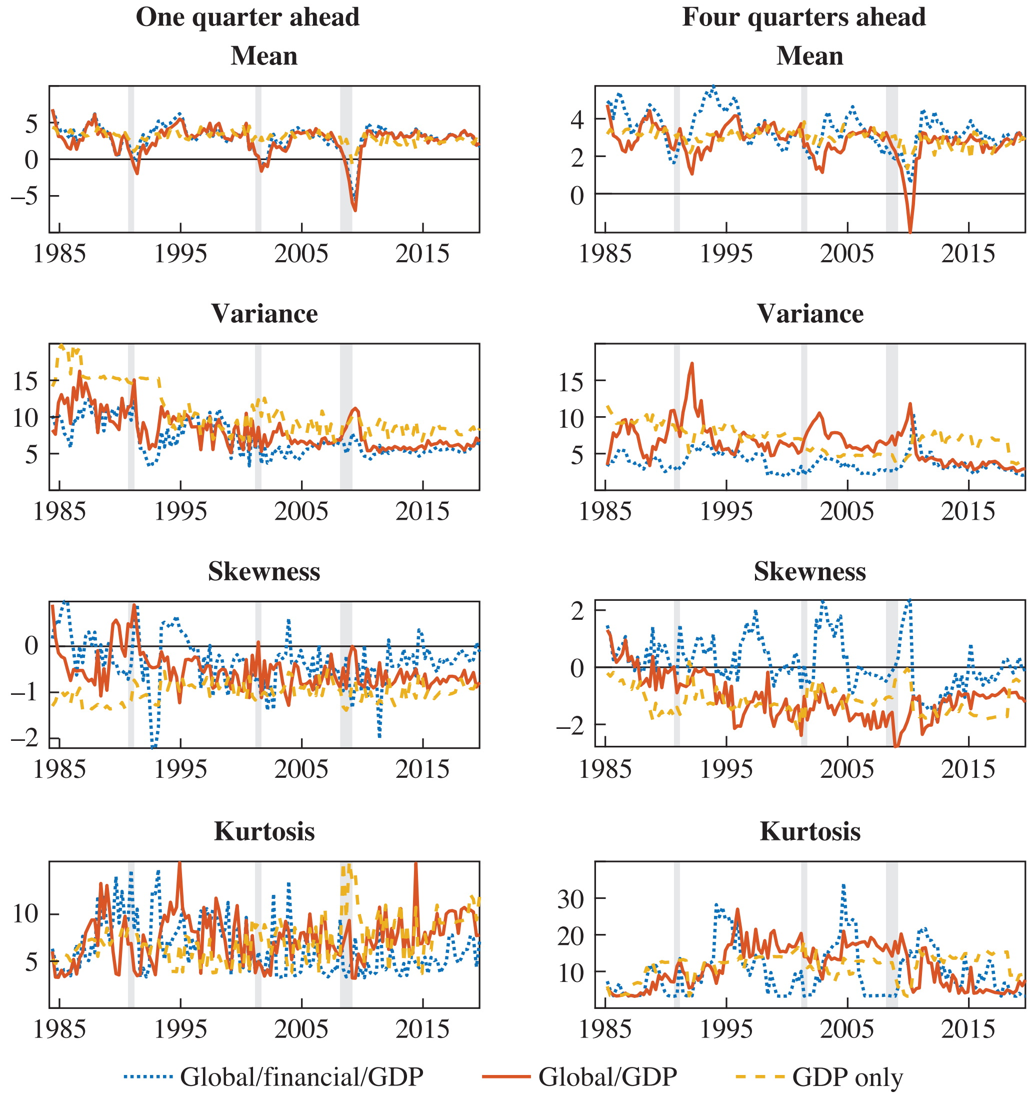
(model 1) GDP growth at time *t*;

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

(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 1975:Q2 to 1984:Q1. 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 2019:Q3. In every quarter of the out-of-sample period, we apply the nonparametric prediction approach of Adrian, Boyarchenko, and Giannone (2019a). 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

Figure 6. Out-of-Sample Forecasts: Time Evolution of the Predictive Distribution of GDP Growth



Source: Authors' calculations.

Note: Time evolution of the four moments of the one-quarter-ahead predictive distribution of GDP growth, from 1984:Q1 to 2019:Q3, for three models: including the global factor, financial factor, and GDP; including the global factor and GDP; and GDP only.

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 online appendix S.A.

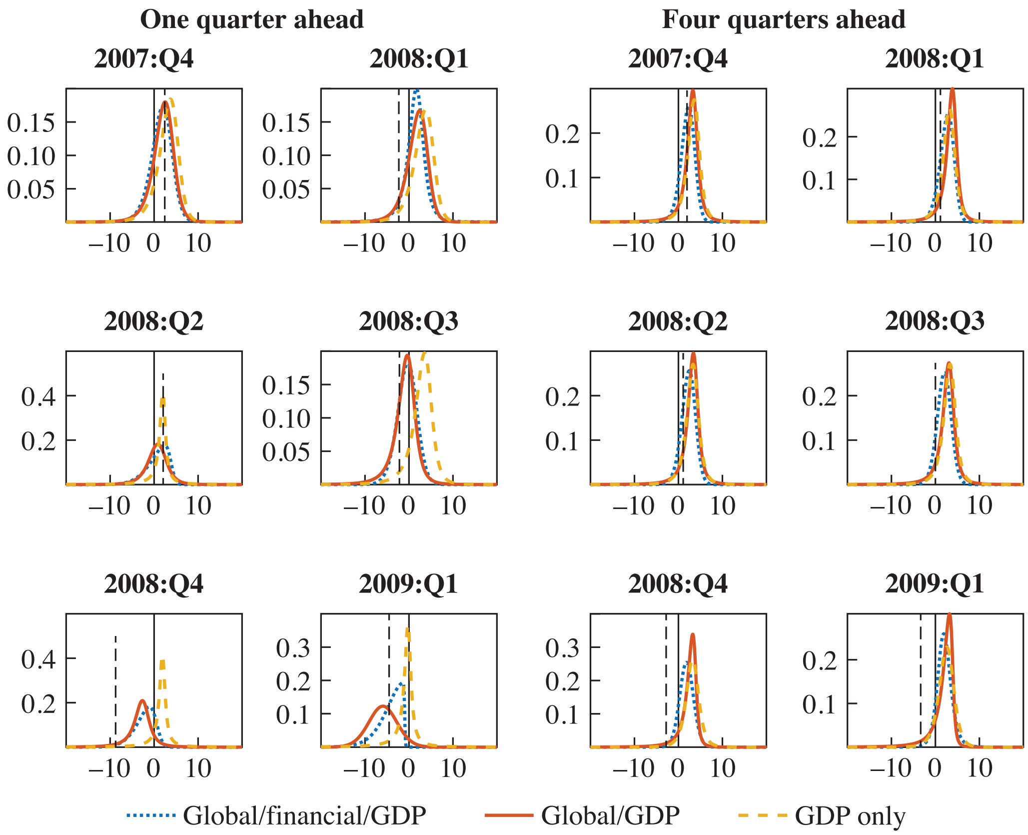
RESULTS Regardless of the predictors used, the models fail to provide noticeable advance out-of-sample signals of the likelihood or severity of recessions. Figure 6 shows the first four moments of the forecast distribution of GDP growth at horizons $h = 1$ and $h = 4$. By breaking down the predictive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

At the one-quarter-ahead horizon ($h = 1$) shown on the left, 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 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 1990s. 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 on the right, 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 (2007:Q4–2009:Q1), for $h = 1$ and $h = 4$, before and during the Great Recession for the three different models. None of the models seem to predict the crisis. At horizon $h = 1$ (the set of graphs on the left), all the models fail to capture the onset of the economic downturn in 2008:Q1, 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 $h = 4$ (the set of graphs on the right), all models seem to do equally poorly in capturing the shift in economic conditions. Although the model that only conditions on lagged GDP performs particularly poorly, the two models

Figure 7. Out-of-Sample Forecasts: Predictive Distributions during the Great Recession



Source: Authors' calculations.

Note: Quarter-by-quarter evolution of the predictive distributions in the period of the Great Recession, from 2007:Q4 to 2009:Q1, for three models: including the global factor, financial factor, and GDP; including the global factor and GDP; and GDP only. The charts report also the realization of annualized GDP growth one and (cumulatively) four quarters ahead, respectively.

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 analyzing the models' predictive scores confirms the minuscule predictive content of the financial factor. This is shown in online appendix S.D in figure S.2. 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 online 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 performance does 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 not to be very informative.[7] 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 turn to nowcasting, that is, 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 macroprudential 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 (Giannone, Reichlin, and Small 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 Archival Federal Reserve Economic Data (ALFRED) database. The data series that we include were chosen to closely resemble the FRED-MD data set, 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

7. This is consistent with the findings of Adrian, Boyarchenko, and Giannone (2019a).

(common to all the variables) and the financial factor (common to the financial variables only and orthogonal to the global factor), we also consider a nonfinancial 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 two-step procedure:

(step 1) We estimate the factors using an expectation-maximization (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; and

(model 3) nonfinancial factor only.

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

Some of the financial variables included in our real-time exercise—stock indexes, 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 online appendix S.B shows all the variables included in the data set, 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

Table 1. Groups of Variables Used in the Nowcast Exercise and Their Release Lags

Variable group	*Release lag*
Stock indexes, exchange rates, interest rates, and spreads	1
Institute for Supply Management indexes	1
Employment and earnings	5
Monetary aggregates	15
Industrial production and subcomponents	16
CPI, producer price index, and subcomponents	16
Housing starts, housing permits, and subcomponents	18
Personal consumption expenditure and real personal income	30

Sources: Archival Federal Reserve Economic Data (ALFRED) and authors' calculations.
Note: 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.

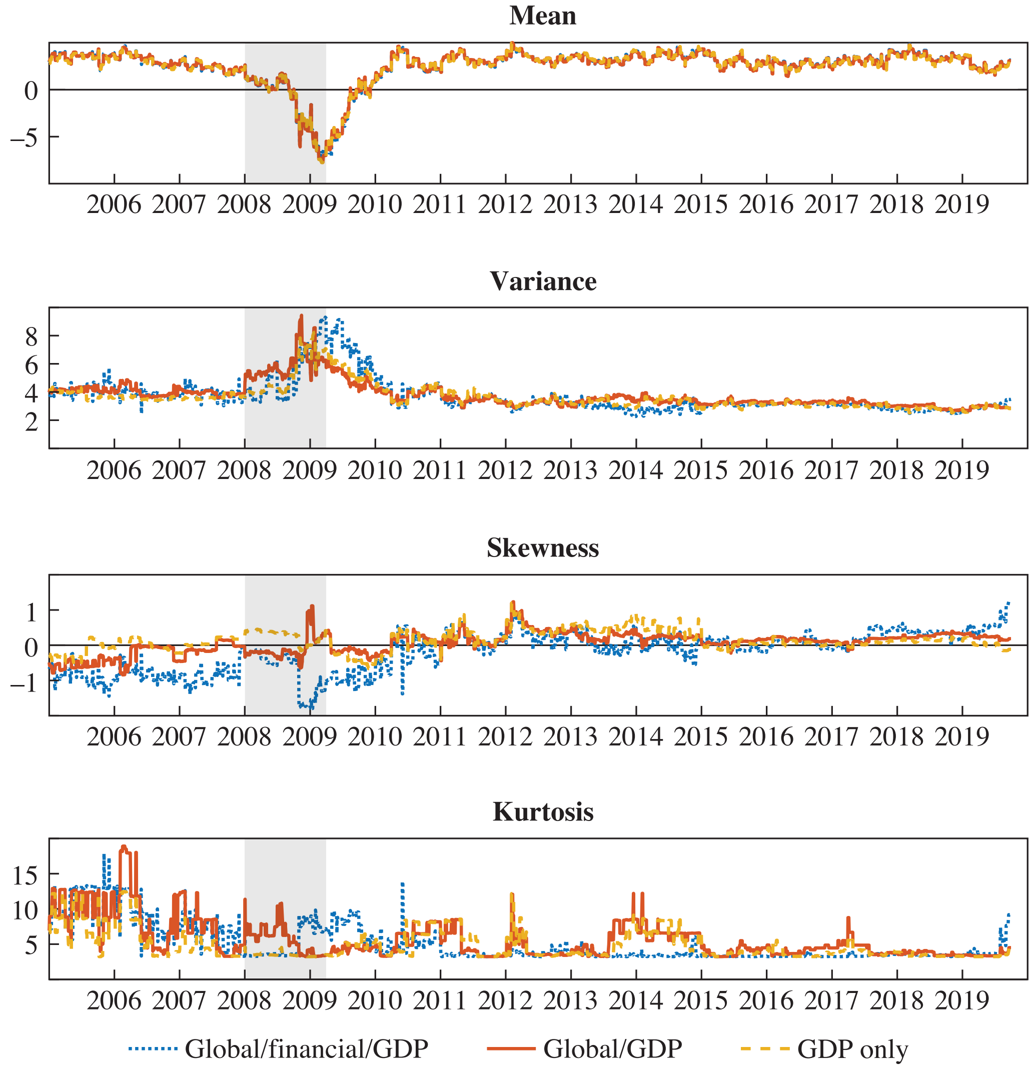
and financial factors allows us to study the additional information content of financial variables over and above what is common to all the other economic variables. Additionally, comparing the short-term forecasting performance of the model that contains only the nonfinancial factor helps assess the 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 that of 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 an increase in kurtosis in 2008 and a spike in skewness early in 2009. While these features are not prominent in the sample, they may be an indication that the real-time model that incorporates financial variables captures 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 chart reports the root-mean-square forecast error of the three models, which depends only on the mean of the predictive

Figure 8. Nowcast of the Moments of GDP Growth

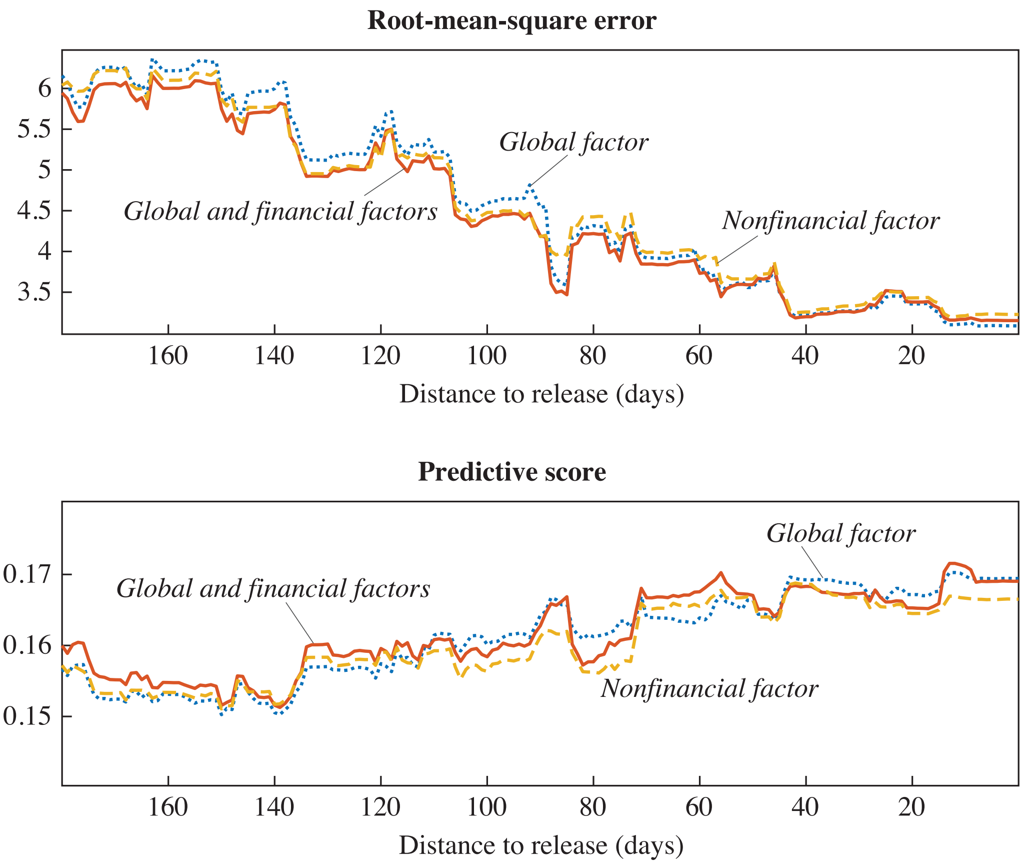


Source: Authors' calculations.

Note: Time evolution of the four moments of nowcast predictive distribution of GDP growth at $h = 0$ of quantile regressions with the global factor only, with the global and financial factors, and with the factor estimated using only nonfinancial variables, from 2005:Q1 to 2019:Q3.

distributions, as a function of the remaining time until data on GDP growth is released. We make the following observations: First, the root-mean-square forecast errors of all three models are on a slightly downward-sloping path throughout the forecasting period. This indicates that the data released over the forecasting period marginally improve the forecasting performance of the model. Second, the root-mean-square 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

Figure 9. Nowcast Evaluation



Source: Authors' calculations.

Note: Both charts show the values over the 2005:Q1–2019:Q3 sample, averaged over the distance to the release date of GDP.

forecast the mean of the growth distribution. Third, 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-square forecast errors of models 1 and 2 (which use financial data) to model 3 (which does not). This is also apparent from the bottom chart, 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 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-square 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 nonfinancial 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 US 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 are 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 1975:Q2–2019:Q2. Online 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's *t*-distribution with ν degrees of freedom, which in turn reduces to the normal distribution when ν approaches ∞. If $\alpha > 0$, the distribution is positively skewed, 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).

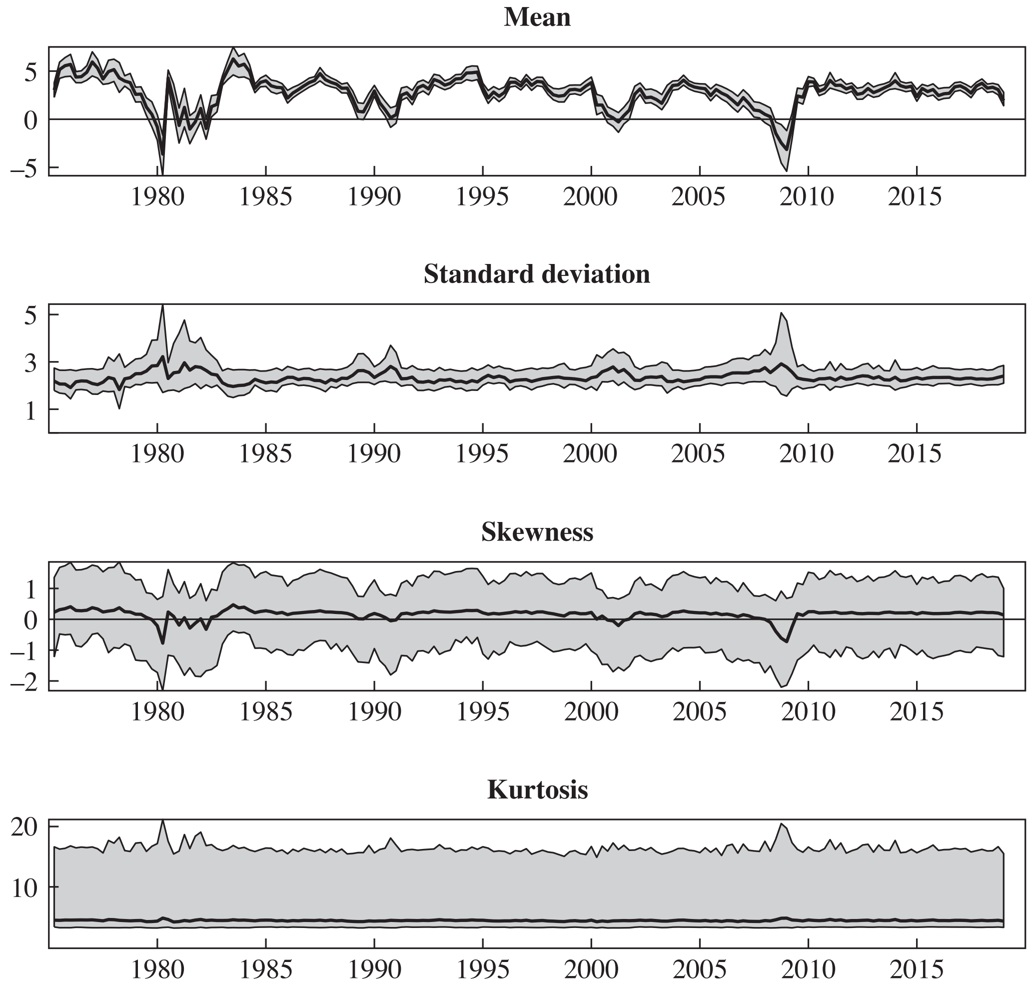
To allow the explanatory variables to influence several features of the GDP distribution, we model the location parameter $\mu = \mu_t$, the logarithm of the scale parameter $\log \sigma = \log \sigma_t$, and the shape parameter $\alpha = \alpha_t$ as being time-varying. These parameters are each assumed 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 online 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, Boyarchenko, and Giannone (2019a) 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 US Moments and Tail Risk

Figure 10 shows that the data are 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 percent 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

Figure 10. US Factor Model: Time-Varying Moments, One Quarter Ahead



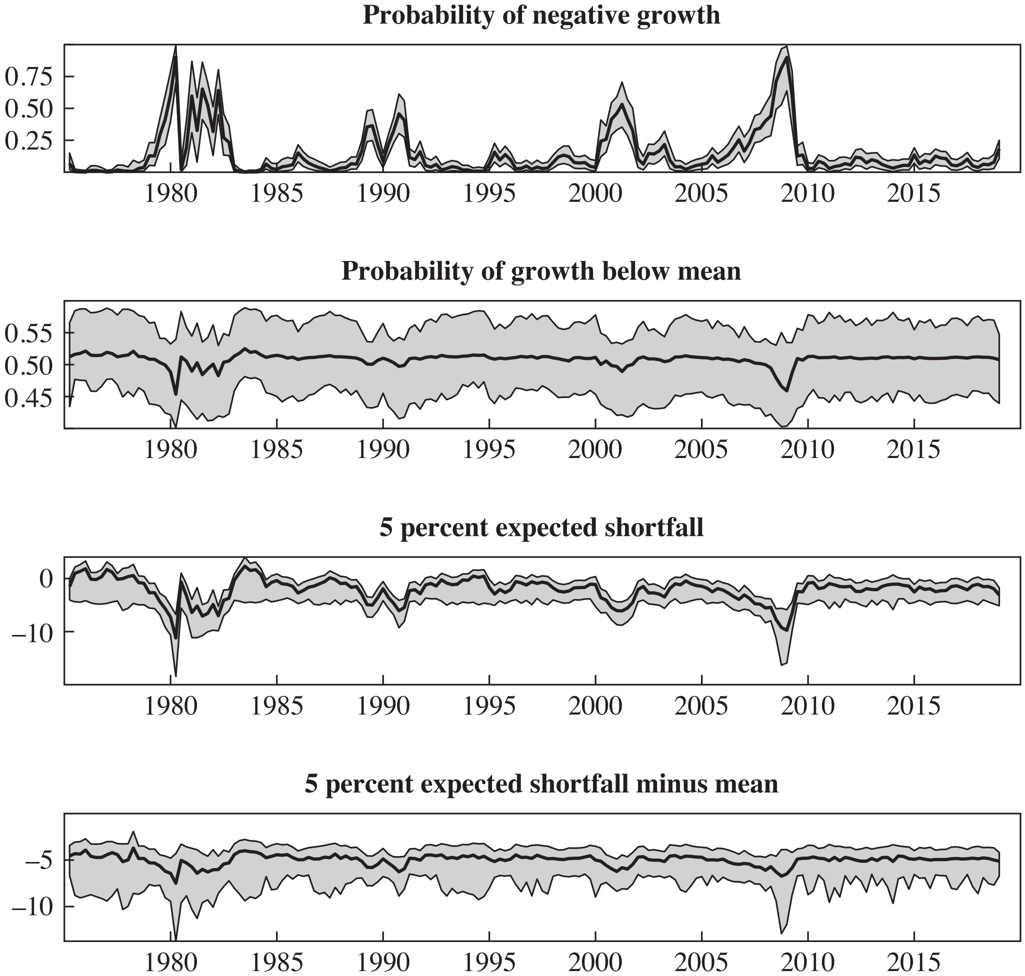
Sources: FRED-QD, FRED-MD, and authors' calculations.

Note: 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 percent posterior credible band (across parameter draws) at each point in time. The time axis shows the quarter in which the forecast is made.

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 online 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 chart in figure 11 shows the time-varying implied one-quarter-ahead conditional probability of a

Figure 11. US Factor Model: Recession Probability and Expected Shortfall, One Quarter Ahead



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

Note: 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 percent posterior credible band (across parameter draws) at each point in time. The time axis shows the quarter in which the forecast is made.

recession (that is, negative growth in 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 chart in 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 chart in the figure shows the 5 percent 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 fifth percentile of its conditional distribution). The expected shortfall moves around over time, but the fourth chart—where the conditional mean has been subtracted—shows that this movement is almost entirely due to movement in the mean. We report analogous results for four-quarter-ahead forecasts in online 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 United States are 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. Online 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 US GDP growth is indistinguishable from zero, but this result masks a subtle feature of the posterior distribution of the underlying model parameters. In online appendix S.F we show that the marginal posterior distributions for the intercepts in the equations for the scale 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 US GDP growth features either a low mean but positive skewness or 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 online appendix S.F that if the model is estimated on the post-1980 sample, the positive skewness mode disappears. Figure 2 shows that US GDP growth was especially erratic in the late 1970s, and indeed growth from 1975 to 1979 has a positive sample skewness. Yet the post-1980 data point quite clearly toward 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 these data are used more intensively. We estimate a global and financial factor separately for each of twelve other OECD countries, using the same method as we used for the United States. Online appendix S.F shows the estimated time-varying forecast moments for Australia, Italy, and Japan, which are representative of the other countries. 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 United States 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 indexes represent the best way to predict and describe growth vulnerability? Policymakers and academics alike may additionally be interested in which specific economic variables carry the most predictive power, for several reasons. First, when designing macroprudential 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 indexes—such as the NFCI used by Adrian, Boyarchenko, and Giannone (2019a)—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 US and cross-country data sets, with a wide array of candidates for 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 United States and for twelve other OECD countries. In contrast to the multicountry analyses of Adrian and others (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 US data set and a multi-country data set for thirteen OECD countries. In addition to GDP growth (the outcome variable), both data sets contain an extensive set of possible predictor variables. The US data set is especially rich and extends back to 1975, while the predictors in the multicountry data set are slightly more limited in scope and extend back to 1980.

The quarterly US data set is based on the Federal Reserve Economic Data Quarterly Database (FRED-QD) data set constructed by Michael W. McCracken and Serena Ng, building on earlier work by Stock and Watson (2012).[8] 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 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, Inc., and Haver Analytics on commodity prices; consumer, business, and purchasing manager surveys; and stock trading volume. This yields a total of forty-three predictor variables.

The multicountry data set covers thirteen OECD countries, with up to thirty-four predictor variables for each country. As in the US 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 straightforward way. The thirteen countries are Australia (AUS), Belgium (BEL), Canada (CAN), Switzerland (CHE), Germany (DEU), Spain (ESP), France (FRA), the United Kingdom (GBR), Italy (ITA), Japan (JPN), the Netherlands (NLD), Sweden (SWE), and the United States (USA).[9] 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, Inc., 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 and others 2018). According to Carmen Reinhart's classification, the United States has undergone only

8. See the Federal Reserve Bank of St. Louis, Economic Research, https://research.stlouisfed.org/econ/mccracken/fred-databases/.

9. Adrian and others (2018) consider the same countries, excluding Belgium and the Netherlands.

two banking crises since 1980: the savings and loan crisis in the late 1980s and the global financial crisis of 2007–10.[10] However, every year from 1980 to 2014, with the exception of 2002–06, has witnessed a new or ongoing banking crisis in at least one of the thirteen countries in our data set. If we include currency crises in the calculation, only the years 2004 and 2006 were crisis-free in all thirteen countries. In an average year, 3.7 countries experience a crisis (standard deviation 2.7). From 1980 to 2016 there have been a total of ninety-nine country-years of banking crises and forty-seven country-years of currency crises for the countries in our data set (just nine country-years experienced both types of crisis at once).

The full list of all US and multicountry predictor variables (and their abbreviations) can be found in online 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, Boyarchenko, and Giannone (2019a).

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, Polson, and Scott (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 toward 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

10. See the data set collected by Carmen Reinhart and colleagues, Harvard Business School, Behavioral Finance and Financial Stability, https://www.hbs.edu/behavioral-finance-and-financial-stability/data/Pages/global.aspx.

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 online appendix S.A.

RESULTS: US DATA We first estimate the model on the quarterly US data set from 1975:Q2 to 2019:Q2. Lagged GDP growth turns out not to be especially important for either the conditional mean or volatility, conditional on the other predictor variables discussed below. Hence, we report the results for the lagged growth coefficients and the intercepts in online appendix S.G.

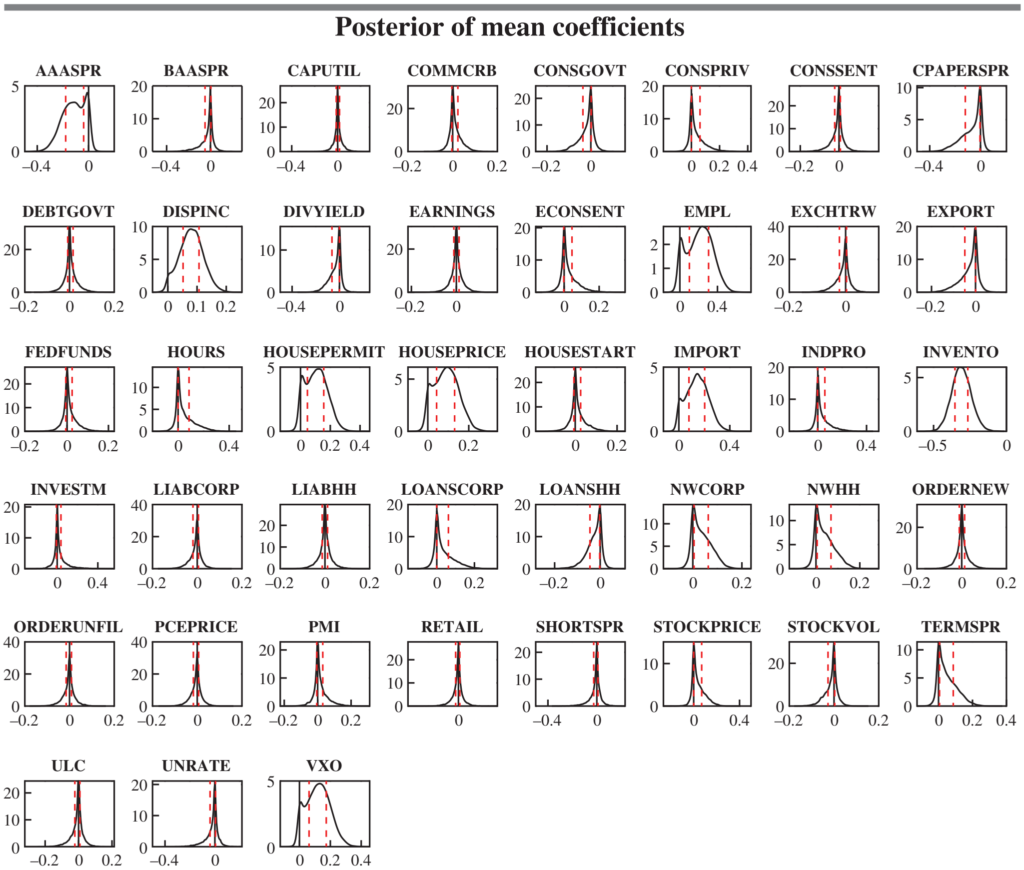
Mean forecasting. Which variables help predict the mean of GDP growth? Figure 12 shows the posterior densities for the mean predictor coefficients. Recall that all predictors have been standardized, so that the magnitudes of different coefficients are immediately comparable. About a third of the variables 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 ten-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.

Volatility forecasting. 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 percent 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 zero.

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

Figure 12. US Conditional Heteroskedasticity Model Posterior Densities

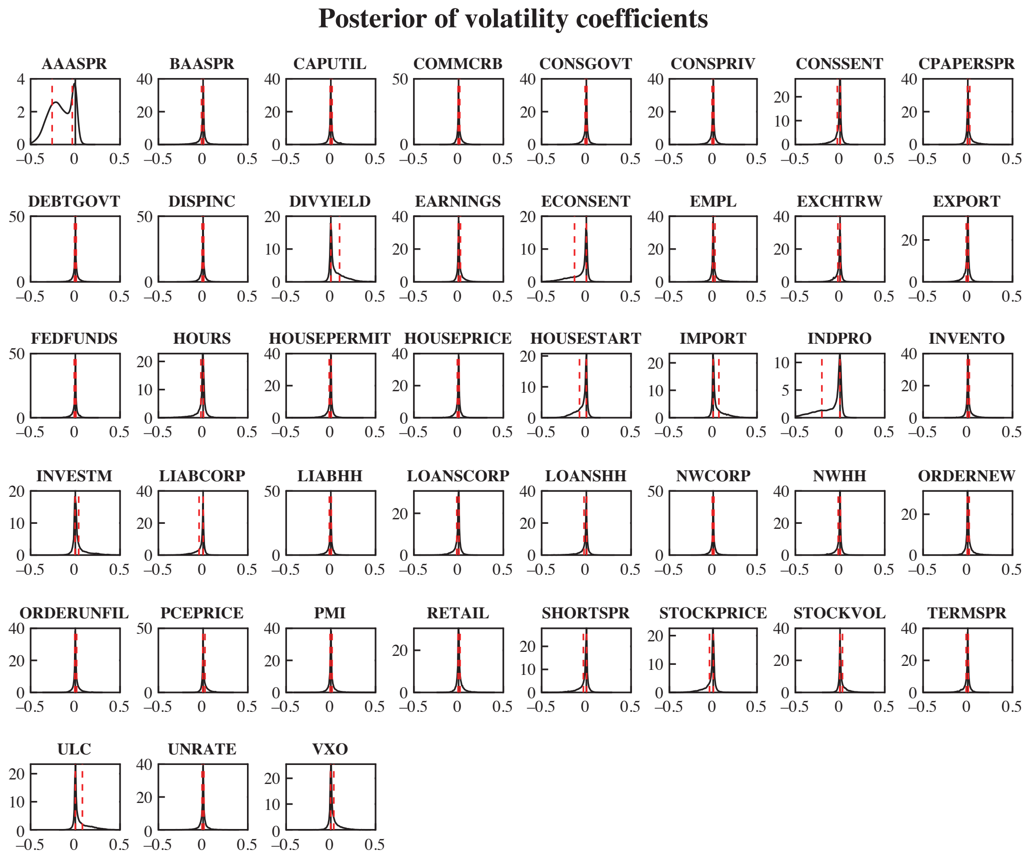


their coefficients exceeding 0.05, or being below –0.05, lies in the range 30–50 percent: business condition surveys (ECONSENT), housing starts (HOUSESTART), and industrial production (INDPRO) all possibly have a negative association with volatility, while the S&P 500 dividend yield (DIVYIELD) and unit 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 percent.

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 thirteen OECD countries from 1980:Q1 to 2018:Q4, 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 US data, the precise identities of the relevant predictor variables appear to be highly heterogeneous across the thirteen

Figure 12. US Conditional Heteroskedasticity Model Posterior Densities *(Continued)*



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

Note: Posterior densities of the coefficients on mean and variance predictor variables in the conditional heteroskedasticity model. Vertical dashed lines indicate posterior interquartile ranges. 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 quarter-on-quarter GDP growth (left, p. 32) or with a 10 percent increase in the conditional volatility of quarter-on-quarter GDP growth (right, above).

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 percent level for more than half the countries (in the sense that the posterior interquartile range excludes zero). The coefficients on consumer sentiment (CONSSENT) and the manufacturing production index (MANUF) also have posterior probability greater than 20 percent (on average across countries) of being larger than 0.1, meaning that a one standard deviation increase is associated with 10 basis points higher quarter-on-quarter 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.

Table 2. Cross-Country Conditional Heteroskedasticity Model: Posterior of Mean Coefficients

		Average across countries			
Variable	*#*[a]	*Median*[b]	*Signif*[c]	*P > .1*[d]	*P < –.1*[d]
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, Inc.; Haver Analytics; and authors' calculations.
Note: Summary statistics of the mean coefficient posterior distributions for thirteen OECD countries.
a. Number of countries present in the data.
b. Posterior median of coefficient.
c. Indicator for whether posterior interquartile range for coefficient excludes zero.
d. Posterior probability that coefficient is > .1 or < –.1, respectively.

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 percent level for more than five 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 a nonnegligible 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 percent 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 ten-year government bond spread vis-à-vis the US (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 United States—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.

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 thirteen 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.

Table 3. Cross-Country Conditional Heteroskedasticity Model: Posterior of Volatility Coefficients

		Average across countries			
Variable	*#*[a]	*Median*[b]	*Signif*[c]	*P > .05*[d]	*P < –.05*[d]
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, Inc.; Haver Analytics; and authors' calculations.

Note: Summary statistics of the volatility coefficient posterior distributions for the thirteen OECD countries.

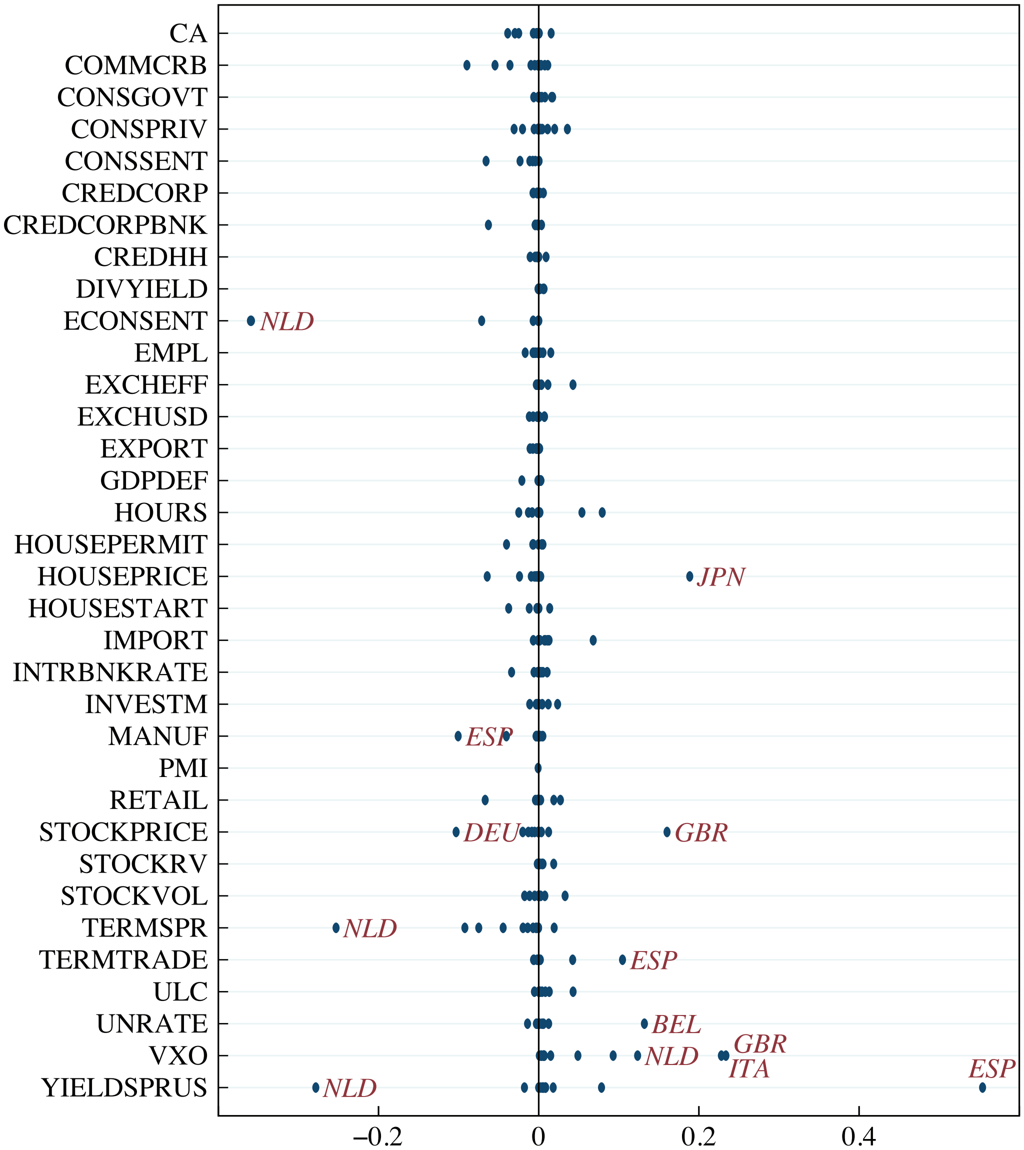
a. Number of countries present in the data.

b. Posterior median of coefficient.

c. Indicator for whether posterior interquartile range for coefficient excludes zero.

d. Posterior probability that coefficient is > .05 or < –.05, respectively.

Figure 13. Cross-Country Conditional Heteroskedasticity Model: Posterior Medians of Volatility Coefficients



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

Note: Each row in the plot corresponds to a variable, while the dots in each row correspond to different countries.

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.[11]

In short, we find little robust evidence of individual predictors being informative about the time variation of skewness. In online appendix S.G we define a measure of the skewness of the forecast distribution with interpretable units, called "TVD." This measure lies between zero and 1, with 1 indicating substantial skewness and zero 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(α_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 percent 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, the Netherlands, and the United States, 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.[12] 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

11. 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 online appendix S.A for details.

12. This is consistent with the conclusion of Adrian, Boyarchenko, and Giannone (2019a, 1276), who however do not report measures of parameter uncertainty.

Table 4. Cross-Country Skew-*t* Model: Unconditional Skewness and Kurtosis

Country	*Avg*(α)[a]	*Avg(TVD)*[b]	*Std(TVD)*[b]	*Q1*(ν)[c]	*Med*(ν)[c]	*Q3*(ν)[c]
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, Inc.; Haver Analytics; and authors' calculations.
Note: Unconditional higher moments of the GDP growth distribution, for eleven OECD countries.
a. Posterior mean of average (across time) of α_t.
b. Posterior means of average and standard deviation (across time) of TVD(α_t), respectively.
c. Posterior first quartile, median, and third quartile of ν, respectively.

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 and others (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 principle generate this empirical pattern if credit growth negatively affects skewness while other financial variables affect the mean 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

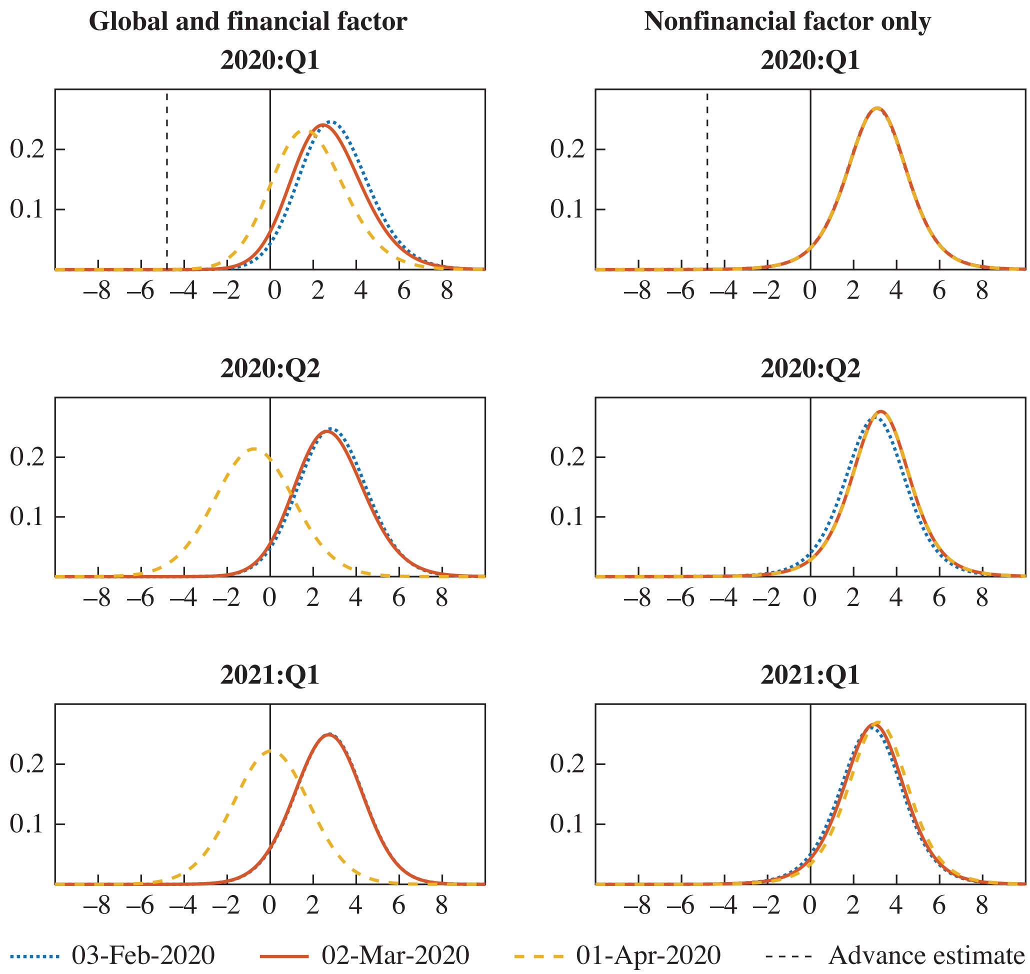
COVID-19 struck the world economy unexpectedly. A sharp recession in the United States, as in other parts of the world, was induced by the lockdown of a large part of the economy. Given the typical delay of macroeconomic information, it has been very difficult for traditional nowcasting and forecasting models to obtain meaningful numbers for the evolution of GDP in the first and second quarters of 2020. The most recent published figure for first quarter growth is –4.8 percent, 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 quarters 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 pandemic 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 macrofinancial common factor (global factor) and the orthogonal financial factor (results are shown in figure 14, left side). The second model conditions on the nonfinancial factor only (figure 14, right side).

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 2020:Q1, 2020:Q2, and 2021:Q1 hardly move at all if we condition only on lagged GDP growth and the nonfinancial 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 1, at that date the only information available concerning March was financial data. At that time, surveys and macro variables were available only for January and February, before the lockdown 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 US 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 in January 2009 when the model updated the estimate for

Figure 14. Predictive Distributions of GDP Growth in the COVID-19 Crisis



Sources: Bureau of Economic Analysis (BEA) and authors' calculations.
Note: Quarter-by-quarter evolution of the predictive distributions for the COVID-19 crisis, for the models including the global factor and the financial factor (left side), and the nonfinancial factor (right side). The charts for 2020:Q1 also report the BEA advance estimate of annualized GDP growth.

2008:Q4, 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 macroeconomic 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 minuscule. 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 are 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 overinterpreted, 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 indexes as catchall 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 be 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 precrisis credit growth can forecast the severity of the crisis. Aikman and others (2016) find that when private nonfinancial 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 and others (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.

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Comments and Discussion

COMMENT BY

MARK GERTLER This impressive paper examines the forecasting power of financial indicators for distribution of GDP growth. The motivation for examining the distribution of GDP growth is that most major financial crises feature sharp nonlinear contractions in GDP. The question then arises as to whether financial indicators can provide an early warning of these economic disasters. Indeed, important recent work by Adrian, Boyarchenko, and Giannone (2019) provides some hope that this may be the case. This work presents evidence that financial variables have predictive power for the lower quantile of GDP growth, which the literature has termed "growth at risk."

Perhaps not surprisingly the present paper provides a "forecaster's perspective." There is considerable emphasis on the statistical significance of the forecast. In addition, the authors focus on the marginal information that comes from financial variables, as I discuss shortly. Given the tough standards they apply, the authors show convincingly that financial variables do not provide significant marginal predictive power for the distribution of GDP growth.

In particular, the authors begin with time series of a large number of real and financial variables. They then proceed to construct two factors. The first is a global factor (GF) that characterizes common movements among the entire set of real and financial variables. Then from the financial variables alone they construct a financial factor (FF). The FF captures common movements in the financial variables that are orthogonal to the GF. In this respect, the FF isolates the marginal information from financial factors.

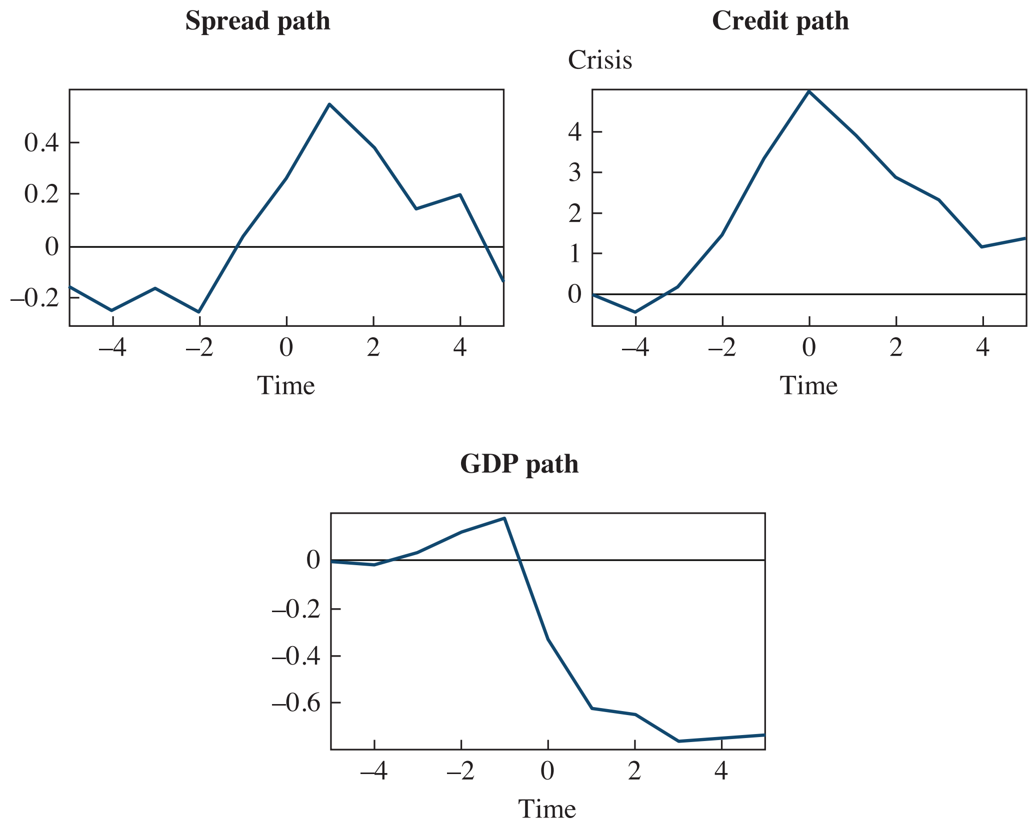
The authors then proceed to assess the predictive power of the FF for the distribution of GDP growth. Here they analyze both out-of-sample forecasting and in-sample parameter uncertainty. There are two main findings. First, it is difficult to predict moments other than the mean, even with the GF. Second, the FF adds little to the forecast. As a check against the possibility that the FF is an imperfect financial indicator, the authors extend the analysis to consider the forecasting power of individual financial variables. They find their result about lack of predictability of financial variables to be largely robust. One important exception, which I return to later, is that credit spreads provide helpful information for near term mean of GDP growth, consistent with results elsewhere in the literature.

TWO CLARIFICATIONS There are two aspects of the analysis that are helpful to clarify. First, the emphasis on the marginal information from financial variables is one important way the paper differs from earlier literature (and could account for some of the differences in findings). In contrast to Adrian, Boyarchenko, and Giannone (2019), the FF excludes the information from the contemporaneous interaction between the financial and real sectors (contained in the GF). By doing so, the authors isolate information from financial conditions that is purely forward-looking. Given the objective of designing an early warning system, that is, a financial siren about risks to future growth that could go off independently of current economic conditions, the authors' approach makes sense. However, as the authors clearly recognize, it is important to keep in mind that their forecasting exercise is silent on the importance of financial conditions for economic activity. Most of the theories of financial–real sector interactions they cite are based on contemporaneous mutual feedback, information that is excluded in their forecasting exercise.

Second, the use of an index for financial conditions that aggregates both credit prices and credit quantities is problematic. Credit prices and quantities differ in cyclical behavior. In particular, credit aggregates tend to oscillate at lower frequencies than spreads. As I show below, they also have a longer lead over real activity than do spreads. In addition, the economic interpretation of quantity and spread behavior can differ, as I also discuss below. In the end, aggregating credit quantity and price information makes the results difficult to interpret. The authors recognize this issue and, as I noted earlier, address it by also considering individual financial variables.

SOME PICTURES TO TELL THE STORY Figures 1 and 2 help illustrate the issues underlying the authors' findings. Figure 1 portrays some basic features of a financial crisis based on evidence from Krishnamurthy and Muir (2017). The data are annual from a panel of industrialized economies from 1869 to 1918. Each panel plots the average behavior of a variable before, during, and after the crisis. The upper right-hand panel shows that roughly three

Figure 1. Behavior of Credit Spreads, GDP, and the Quantity of Credit

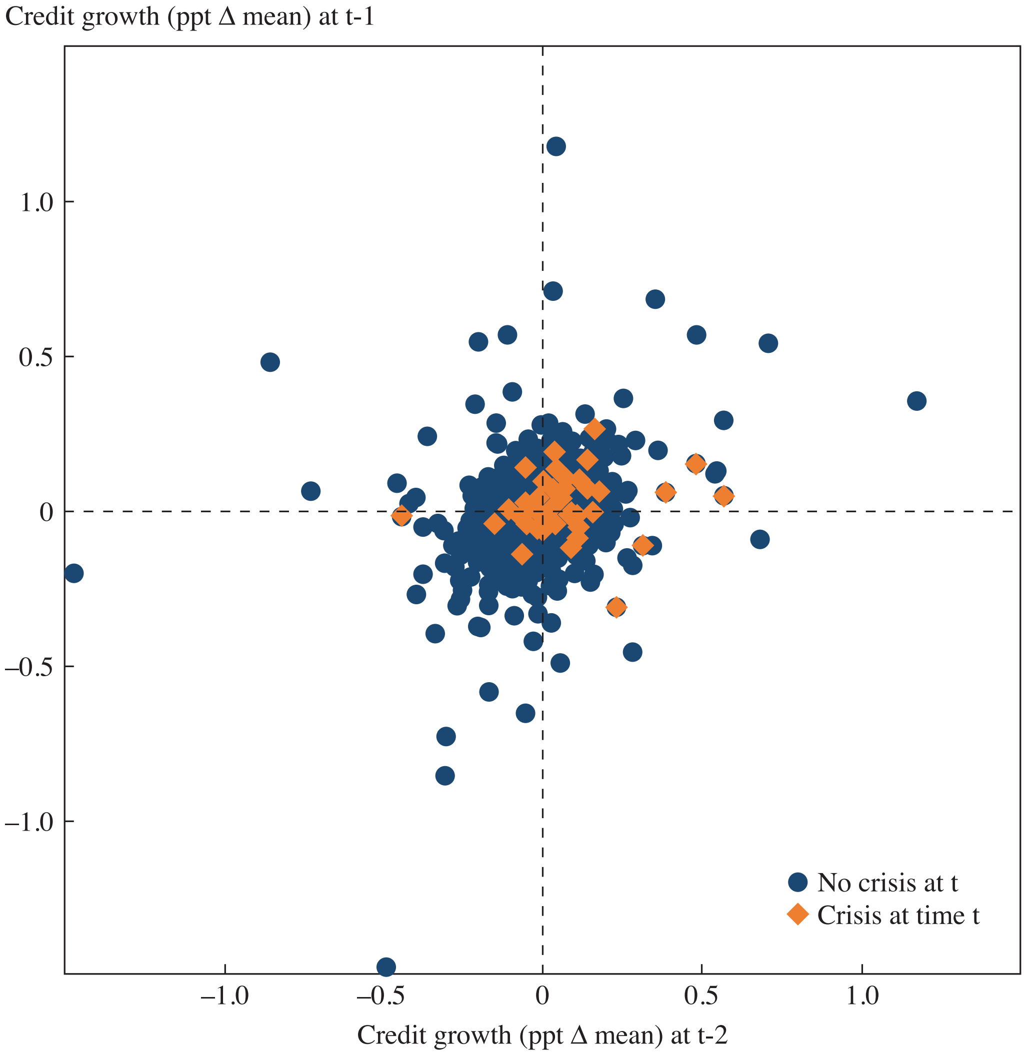


Source: Krishnamurthy and Muir (2017).

Note: This figure plots the behavior of credit spreads, GDP, and the quantity of credit around a financial crisis with the crisis beginning at time zero. GDP and credit are expressed in deviation from (country specific) trend. Spreads are normalized by dividing by the unconditional mean.

years prior to a crisis a credit boom emerges (typically associated with increasing asset prices). The upper left-hand panel shows that roughly two years later, on the eve of the crisis, credit spreads increase steadily and peak just following the crisis. From the lower panel, we see that there is a mild output boom entering the crisis followed by a sharp contraction. The figure clearly reveals nonlinear behavior of output in a financial crisis. It also shows the distinct patterns of credit aggregates and credit spreads. The former tend to exhibit a longer lead over the crisis than the latter. A natural interpretation is as follows. The buildup of credit (and leverage) increases borrowers' vulnerability to negative shocks. When negative shocks (e.g., declining asset prices) eventually occur, borrower balance sheets weaken and financial distress emerges. Credit spreads reflect this distress. The important point to note is that while credit quantity and spreads play interrelated roles in the crisis, their timing and economic

Figure 2. Credit Booms and Financial Crises



Source: Gertler, Kiyotaki, and Prestipino (forthcoming).
Note: Run Frequency after boom: 4.9 pct.; After no boom: 2.8 pct.; (Boom: top right quadrant).

relevance is distinct. For this reason, financial indexes that aggregate both types of variables may not provide the most efficient use of information.

Figure 2, taken from Gertler, Kiyotaki, and Prestipino (forthcoming), illustrates why it may be difficult to find a reliable early warning signal of a financial crisis, despite the evidence in figure 1 that credit growth tends to lead crises by at least several years. The central identification problem is that there are "good" credit booms as well as "bad" ones, with the former being far more prevalent than the latter. The horizontal axis in figure 2 is demeaned credit growth for a country two years prior to current time. The vertical axis is demeaned credit growth one year prior. We can then define a credit boom as two years of above average growth, which corresponds to the upper right-hand quadrant in the figure. The diamond-shaped dots in the figure are times within a country where a crisis occurred. while the round dots are times absent a crisis. The key message is that conditional on a credit boom (i.e., conditional on being in the upper right-hand quadrant) crises occur only 5 percent of the time. That is, most of the time credit booms are good. It is true that a crisis is more likely conditional on boom. Conditional on no boom a crisis occurs with only 2.8 percent probability. The bottom line, however, is that credit growth is unlikely to provide a reliable early warning signal.

Credit spreads are likely a more reliable indicator than credit aggregates. However, as figure 1 shows, the lead time of a spike in spreads over a crisis is typically much shorter than that of credit growth. Thus, spreads are unlikely to provide a lengthy advance warning of the crisis. Nonetheless, the authors do present evidence that, for the near term, spreads help forecast the mean of GDP growth, which is consistent with results elsewhere in the literature.

One caveat the authors note is that spreads do not provide information about the higher moments of GDP growth. Nonetheless, spreads may provide information about the depth of a recession. The reason is that spreads exhibit asymmetric positive jumps on the eve of crises that mirror the asymmetric declines in output, as figure 1 makes clear. A large jump in the spread prior to a crisis, accordingly, predicts a large drop in the conditional mean of output growth, everything else being equal.

A FEW THOUGHTS GOING FORWARD As the paper makes clear, a central challenge in forecasting the distribution of GDP growth involves data limitations. There are simply not enough data to get statistical precision in the link between financial indicators and the higher moments of GDP growth. In the case of the United States, there has been only one major financial crisis in the postwar period (though that may change depending on how the current crisis plays out). To be sure, financial stress has occurred in previous downturns, but not on the same scale. One possibility, which the authors pursue at the end of the paper, is to exploit international data. The advantage, of course, is that they will gain more observations on financial crises. Here they find only very limited success: credit spreads are helpful in forecasting mean GDP growth (as noted earlier), but otherwise financial variables have little information content about GDP. As the authors note, though, more needs to be done to account for country heterogeneity.

It might also be useful to consider alternative financial indicators. For example, Krishnamurthy and Muir (2017) find success by interacting credit

Figure 3. Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity

Source: Federal Reserve Economic Data (FRED).

aggregates with credit spreads. Another interesting possibility might be to disentangle unusual periods of high credit growth from normal periods of robust growth, as done by Hasenzagl, Reichlin, and Ricco (2020). Here, though, it might be necessary to make use of international data, given the limited number of such episodes in the United States.

BRIEF OBSERVATIONS ON FINANCIAL INDICATORS IN THE CURRENT CRISIS By mid-March, when it was obvious that the pandemic was going to have a clear economic effect, credit spreads increased sharply. The Baa corporate bond spread, as portrayed in figure 3, rose sharply from 200 basis points to nearly 425 basis points. This was below the peak of the Great Recession but at the same level at similar stages of the recession. Other financial indicators also pointed to distress, including plunging stock prices, various measures of liquidity in bond markets, and an increasing VIX. In this regard, financial variables were incorporating news of the contraction that would follow.

Were it not for an aggressive intervention in financial markets, financial market conditions would likely have continued to deteriorate sharply. Among other things, the Federal Reserve committed to buying high-grade corporate bonds with the backing of the Treasury. In the period following the announcement, corporate spreads have declined roughly 100 basis points and other financial distress measures have receded as well. For our purposes, the key lesson is that by (appropriately) taking action to reduce spreads the Federal Reserve has likely reduced the information content of this variable.

CONCLUDING REMARKS This paper makes a convincing case that the marginal information that financial variables have for the distribution of GDP growth is minimal. It is well executed and a very useful contribution to the forecasting literature.

As the authors would agree, though, lack of forecasting power is not the same thing as lack of importance for real activity. Much of the real–financial interaction is contained in the contemporaneous interaction between real and financial variables, which is excluded from the authors' definition of marginal financial information.

The key lesson for policy is that macroprudential policy should not be based on predictability. Rather, it should design the best response to unpredictable shocks that disrupt the financial system. This design, further, will most certainly depend on financial variables (e.g., bank leverage ratios, liquidity measures, etc.).

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COMMENT BY

NELLIE LIANG This paper tackles two broad questions: Do financial variables have predictive value for GDP growth, and can higher moments of the GDP growth distribution be predicted? It is a forecasting paper, and it is extensive. The authors argue that financial variables have no predictive power for GDP growth or risk to growth. But the paper misses the broader and more important relationship between the financial sector and real economy, which I discuss below and illustrate with the example of recent Federal Reserve actions in response to COVID-19.

I agree with the authors' point that financial variables cannot be reliable predictors of a crisis, like one brought on by a pandemic or even the 2008 global financial crisis. A crisis represents the product of a negative shock and vulnerabilities, which are amplifiers of shocks. To predict a crisis, financial variables would need to be able to predict both a negative shock and financial vulnerabilities. And they are not better at predicting a shock than any other variables.

But the message of the paper should not be that financial variables are not useful indicators of vulnerabilities in the financial sector because they can't predict shocks. It would be a mistake to suggest that policymakers can ignore the effects of financial variables on the economy.

Financial stability reports of central banks are designed to guide macroprudential policies and to be inputs into monetary policy and emergency liquidity actions. The reports are very careful to say they cannot predict the next crisis, but they highlight the conditions that make the economy more prone to a crisis or deep recession because financial vulnerabilities are high and could amplify any unexpected negative shock through fire sales or contagion. Macroprudential policies aim to preemptively reduce financial vulnerabilities, like raising capital requirements for banks when credit is booming so that banks will have additional capital buffers to absorb higher future losses and be able to continue to provide credit should there be a negative shock. Indicators of financial vulnerabilities are financial variables, like asset valuations, credit burdens of borrowers, and leverage and funding risks of financial intermediaries. But in this paper the authors argue that financial variables have no predictive power and convey a message based on that narrow framing that they have no value for thinking about economic risks.

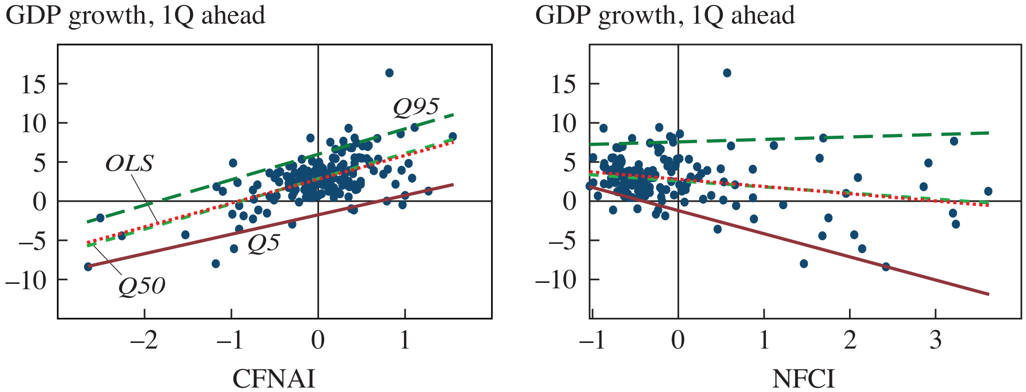
In its May 2020 financial stability report, the Federal Reserve highlights how some hedge funds and private mortgage funds quickly sold assets after asset prices fell in response to the spread of COVID-19. These sales contributed to unusual market dysfunction in the US Treasury and mortgage-backed securities markets as bid-ask spreads widened and market depth shrank. Had financial regulators been willing or able to take more forceful macroprudential actions in recent years to limit the systemic consequences of leverage, liquidity risk, and model-driven strategies of some private funds, the fall in asset prices brought on by the pandemic (which could not be predicted) would not have been amplified to such an extent and could have limited purchases of Treasury securities and residential and commercial mortgage-backed securities by the Federal Reserve in March. (Those purchases were emergency liquidity actions, not quantitative easing or macroprudential actions.) The point is that financial vulnerabilities can have significant consequences for growth and risks to growth.

The authors argue that financial variables have no predictive power for GDP growth or risk to growth because "markets do not anticipate the timing of [a] recession and they price the risk only once they see it." This statement highlights the framing of their empirical analysis, that financial variables are valuable only if they can predict shocks that can lead to recessions before real data can predict them. For several reasons and illustrated above with a specific example, I think the framing in the paper is too narrow. First, it ignores a more relevant question for financial policymaking of whether financial variables affect risk-taking behavior of borrowers and lenders which lead to financial vulnerabilities. The importance of behavioral effects, indeed the endogeneity of financial variables and real activity, is a primary lesson of the global financial crisis and is core to macroprudential policymaking. That is, financial conditions can affect the buildup of financial vulnerabilities which can amplify large negative shocks, such as the recent COVID-19 pandemic. These amplification effects show through as financial market dysfunction and restricted credit supply which can separately increase risks to growth.

A second reason is that here the authors use a broad activity indicator that includes both real and financial variables, as well as price and monetary policy variables, and then evaluates whether a separate financial variable constructed to be orthogonal to the broad indicator has additional predictive value. This unique construction leads to a financial factor that differs from most others and may be biased against finding value in financial variables leading to findings that seem to differ from those in a growing list of other studies. Third, when evaluating whether individual indicators might be significant rather than indexes, the authors do not distinguish between types of financial variables. That is, the tests are horse races of variables without imposing any structure, which the authors acknowledge. But many papers find that the effects of different variables differ significantly, because funding risks will be different from the effects of credit risk and from the effects of financial intermediary risks.

In my discussion below, I focus on the results and interpretation related to forecasting the mean and variance of the US real GDP growth distribution

Figure 1. Quantile Regressions of GDP Growth on Real Activity and Financial Conditions Indexes



Source: Author's calculations.

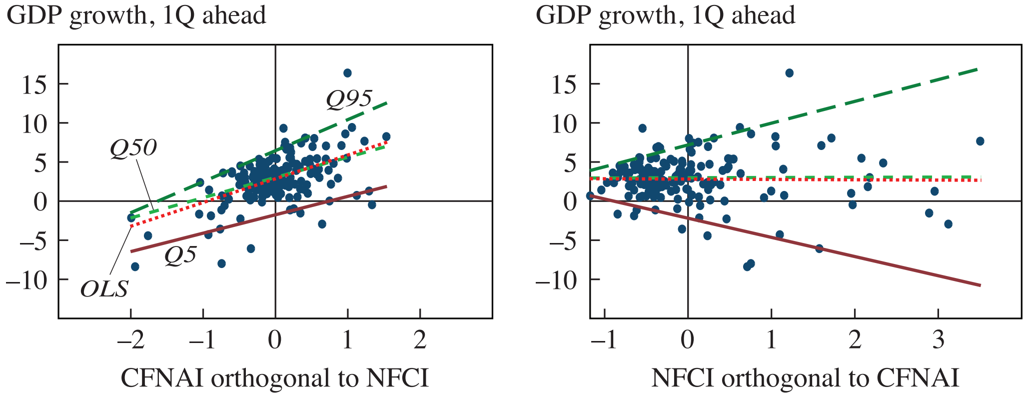
and interpret the results in terms of implications for macroprudential policy. The empirical results on skewness and kurtosis, as well as forecasts for other countries, do not change their broad conclusions.

To illustrate the issue of whether financial variables offer any additional information above the content in real activity variables, I estimate quantile regressions for GDP growth one quarter ahead on two indicators, an index of real economic activity (Chicago Fed National Activity Index, CFNAI) and a separate financial conditions index (NFCI). Both indexes are constructed by the Federal Reserve Bank of Chicago and allow the estimation period to start in 1975. In figure 1, I show the scatterplots of GDP growth one quarter ahead plotted, first, against the index of real economic activity and, second, against the financial conditions index. The lines in the plots are slopes of the quantile regressions. In contrast to ordinary least squares, quantile regressions minimize the absolute deviation rather than squared deviation of errors; this has the effect of weighting errors more heavily near the quantile of interest than errors that are further away.

As shown, the median quantile for GDP growth one quarter ahead for the real activity index (CFNAI) has a positive slope, and the slopes for the fifth percentile and the ninety-fifth percentile are similar, suggesting the variance is constant across different activity levels.

For the financial conditions index (NFCI), the slope of the median is slightly negative (tighter financial conditions in the current quarter, lower GDP growth in the next quarter). In contrast to the results for CFNAI, the slope of the fifth percentile is much more negative than for the median.

Figure 2. Quantile Regressions of GDP Growth on Orthogonal Real and Financial Conditions Indexes



Source: Author's calculations.

These slopes are statistically different. They show the variance differs, although there clearly are fewer data points at higher levels of the NFCI, when they are tighter and GDP growth one quarter ahead is lower.

The next two charts in figure 2 illustrate the same relationships but are based on indexes now constructed so they are orthogonal to each other. The quantile regression slopes of the real activity index that is purged of the financial index and GDP growth one quarter ahead does not change. The slopes of the NFCI purged of the real index to GDP growth one quarter ahead also do not change much. The fifth percentile remains more negatively related to financial conditions than the median, and the coefficients are statistically different.

These charts are a straightforward way to illustrate that financial variables do matter for variance once real activity variables are included. This real activity index does not include financial variables, and so a financial indicator orthogonal to the real index still has predictive value. In contrast, in this paper the authors use a global factor, which is common to all 112 variables in the FRED-MD data set, which are real, price, monetary, and financial. The financial factor is constructed from the financial variables but also orthogonal to the global factor. A financial factor is then interpreted to be important only if it is important separately and in addition to its role in the global factor.

A number of studies other than Giglio, Kelly, and Pruitt (2016) and Adrian, Boyarchenko, and Giannone (2019), which the authors cite in the paper, have found significant effects of various financial variables on GDP risk in the United States. For example, Coe and Vahey (2020) use non-Gaussian and nonlinear estimations to predict risk to growth in the four crisis periods since 1875; Kiley (2018) uses quantile regressions to predict risks to the unemployment rate in the United States; Carriero, Clark, and Marcellino (2020a) and Caldara, Scotti, and Zhong (2020) use vector autoregression models with stochastic volatility to capture tail risks; and Carriero, Clark, and Marcellino (2020b) test a number of alternative models and show that a number of financial variables improve both point and tail risk nowcasts of GDP. Financial variables have been found to be significant for risk in other countries as well, in work by Chavleishvili and Manganelli (2019) for the euro area and Duprey and Ueberfeldt (2020) for Canada.

The authors also evaluate the time-varying distribution of GDP growth and find that parameter uncertainty around time-varying moments other than the mean are imprecisely estimated. While the standard deviation of GDP growth one quarter ahead clearly varies over time, and in line with the mean, the paper shows it has high parameter uncertainty around recession periods. The authors emphasize that the variance cannot be estimated precisely and the financial factor is not important. I would emphasize instead the finding that the GDP growth distribution is time-varying and that periods when uncertainty is higher—the recessions—are precisely the periods we care most about. Rather than concluding it is a futile exercise to estimate these periods, I think a more appropriate interpretation is that more work is needed to help predict these important events.

One extension could be to draw on research that distinguishes financial indicators by specific concepts they are intended to measure. To illustrate, Bernanke (2018) uses daily data on seventy-five financial variables and aggregates them to a monthly frequency to evaluate the effects of financial variables on mean GDP growth. Importantly, he splits the data to represent four groups, reflecting housing and mortgages, nonmortgage credit availability, short-term funding, and bank solvency. He finds the effects of the four factors vary significantly: panic factors (credit and funding) are significant predictors of the means of monthly GDP, industrial production, the unemployment rate, and other variables, whereas the balance sheet factors are less significant. He does not test for variance, but the sample period contains only one recession.

Many papers that have studied the role of credit on large output losses in the future have incorporated credit cycles of many years because cycles can take a while to emerge. For example, Jordà, Schularick, and Taylor

(2013) focus on credit growth since the trough of the last recession, and Kiley (2018), Aikman and others (2020), and Adrian and others (2018) use between eight and sixteen quarters to capture credit cycles. In a separate paper, Hasenzagl, Reichlin, and Ricco (2020) show that the leverage subcomponent can help to predict the variance of quarterly GDP growth, while the subcomponents for market and credit risk do not. This type of analysis is missing in this paper.

In a third stage of the analysis, the authors test the predictive value of individual financial variables for the distribution of GDP growth. They use data in FRED-QD and add some additional data. The data set for the United States has forty-three variables, of which fifteen are financial variables, a mix of quantity and price variables. The authors employ a conditional heteroskedasticity model for GDP growth and a method that selects the relevant predictor variables among a large set of variables using a "Bayesian prior distribution on the model parameters that imposes approximate sparsity." Each of the variables are entered separately. They find that only a couple of financial variables can help to predict mean or variance, though perhaps this is not surprising given many of the variables are collinear and they are not grouped in any way.

What does this paper suggest for macroprudential policy? Macroprudential policies are designed to increase the resilience of the financial sector to negative shocks, to reduce amplification because disruptions in credit and funding can have serious repercussions for the real economy. Financial variables can help macroprudential policymakers for what they signal about possible buildups of financial vulnerabilities when financial conditions allow lenders and borrowers to increase risk taking by more than usual, which would make the financial system more vulnerable to negative shocks. Financial variables can also signal possible disruptions in market liquidity and credit supply which if sustained would increase risks to growth as borrowers lost access to credit.

The authors acknowledge that there is a role for macroprudential policies because financial vulnerabilities can amplify shocks. But their results aren't directly applicable because they test the value of financial variables mainly as noisy predictors that are just a reflection of real activity, rather than an assessment of current and potential buildup of financial imbalances.

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GENERAL DISCUSSION James Stock thanked the authors and discussants for a great paper and informative discussion. He said he was sympathetic to the challenge of having to make forecasts of not just GDP but also its moments using financial variables. He wondered why the authors' results differed so much from those of Adrian, Boyarchenko, and Giannone.[1] He asked whether the distinctions were due to differences in methods or indexes.

Lucrezia Reichlin pointed out she had recently used exactly the same data as Adrian, Boyarchenko, and Giannone to test the performance of financial variables in out-of-sample forecasting in a paper together with Ricco and Hasenzagl.[2] This paper found similarly negative results about the ability to forecast GDP using financial variables, so the difference could not be the data. Instead, the authors' results differ substantially from those of Adrian, Boyarchenko, and Giannone because of how the global and financial indexes are constructed, she said. Several financial indexes, like the Chicago Fed's National Financial Conditions Index, are actually very correlated with real factors. This fact motivated the authors to construct a financial index that separates out all of the effect of real variables to answer the question: How much additional predictive power does the purely financial component of the movement in financial variables give you? As it turns out, the answer is not much.

Nevertheless, Reichlin agreed with Liang's point that financial variables are very important for the business cycle. But much of that effect works endogenously through common factors captured by the authors' global factors. Reichlin noted that the authors take a "brain-dead forecasters" approach, ignoring any structural mechanism relating financial and real variables, and focus purely on the usefulness of their financial factors for forecasting GDP and its moments. They would need to take a different, more structural, approach to get at the endogenous mechanisms driving the effect of financial variables on business cycles, Reichlin said.

Giovanni Ricco noted that both Liang and Gertler questioned whether it was possible to cleanly separate real and financial shocks in their discussions. Ricco responded that their paper does not perform a fully structural exercise, and a structural model is needed to get at the mechanisms through

1. Tobias Adrian, Nina Boyarchenko, and Domenico Giannone, "Vulnerable Growth," *American Economic Review* 109, no. 4 (2019): 1263–89.

2. Lucrezia Reichlin, Giovanni Ricco, and Thomas Hasenzagl, "Financial Variables as Predictors of Real Growth Vulnerability," Discussion Paper 05/2020 (Frankfurt: Deutsche Bundesbank, 2020), https://www.bundesbank.de/resource/blob/827682/3deb1560a27f63fe08d2f60628eb7636/mL/2020-03-05-dkp-05-data.pdf.

which financial and real variables interact. Having said that, the starting point of their paper was that movements in financial variables reflect some mixture of information about developments in the real economy and extra financial stresses. This motivated them to take the admittedly extreme approach of removing all of the global and real factors and to instead work with just the orthogonal financial component. This decision allowed them to analyze whether the financial component had additional predictive power. If so, this finding would provide strong reduced form evidence in favor of an additional financial frictions story. However, their results indicate that their index does not have much predictive power. Ricco noted that this result is not the end of the story. He noted that extending the analysis with more structural guidance is necessary for thinking about policy.

In response to Liang's point that estimates of the standard deviation of GDP do move around over time, Ricco pointed out that while it is true that their point estimates move around, it is still possible to draw a flat straight line through their uncertainty band. While their paper shows that it is certainly true that financial variables have some predictive power for the variance of GDP, Ricco observed that overall the results on the second moment showed a very weak predictive relation.