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Forecasting macroeconomic risk in real time: Great and Covid-19 Recessions

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Abstract

We show that financial variables contribute to the forecast of GDP growth during the Great Recession, providing additional insights on both first and higher moments of the GDP growth distribution. If a recession is due to an unforeseen shock (such as the Covid-19 recession), financial variables serve policymakers in providing timely warnings about the severity of the crisis and the macroeconomic risk involved, because downside risks increase as financial stress and corporate spreads become tighter. We use quantile regression and the skewed t-distribution and evaluate the forecasting properties of models using out-of-sample metrics with real-time vintages.
Keywords: Non-linear models, Great Recession, Covid-19 Recession, Downside risks, Real-time forecast.

JEL classification: C53, E23, E27, E32, E44.

Non-technical summary

The analysis of downside risks to economic growth is central in real-time macroeconomic forecasting, because the weakening of economic activity can manifest itself in the volatility and the left-skewed GDP growth distribution, even if the forecast of real GDP growth's conditional mean remains unchanged. Forecasting the higher moments is of paramount importance, because often policymakers justify a neutral monetary policy stance or conduct an expansionary monetary policy referring to risks to the economic activity titled to the downside. This paper addresses the question whether financial variables can help predict in real-time macroeconomic risk once controlling for macroeconomic factors. The analysis is undertaken around the two biggest recession periods that the United States (US) phased after the Second World War: the Great Recession, which according to the NBER (US National Bureau of Economic Research) started in December 2007 and ended in June 2009, and the Covid-19 Recession in 2020, which according to the NBER started in February 2020.

Both recessions were not foreseen by policymakers as well as the majority of academic and professional economists. Using real-time vintages, we show that financial variables forecast the Great Recession (first moment) and the associated macroeconomic risk (higher moments) already at the beginning of 2008. As for the Covid-19 Recession, though it was not expected in the US on March 15, 2020, the same financial indicators forecast negative growth and a sharp downside in macroeconomic risk already in the first week of March, while established macroeconomic factors show the economic damage wrought by the coronavirus crisis after the unprecedented drop of the US Markit flash Composite Purchasing Managers Index Output (henceforth, PMI) on March 24 and the fall in US nonfarm payroll by 701.000 in March released on April 3. Against this background, the FED has cut its benchmark interest rate by 50 basis points on March 3, 2020, uniquely focusing on the information from financial markets, followed by an additional 100 basis points cut on March 15, 2020. Therefore, the results of this paper, obtained using real-time data, are comforting. The Covid-19 recession is truly an unexpected event. Financial variables have served policymakers early in March 2020, providing timely warnings about the severity of the crisis and the macroeconomic risk involved.

We address the question focusing on key specific macro and financial variables, which are typically and widely used in the profession. The main analysis is carried out employing the PMI for the US compiled by IHS Markit, the US Composite Indicator of Systemic Stress (CISS) compiled by the ECB and corporate spreads of investment grade bonds issued by US non-financial corporations. The advantage of the PMI is that its flash estimates are available already 7-10 days before the end of the current month and, as a result, it is the first major survey-based macroeconomic indicator to provide evidence of a sharp drop in economic

activity globally in March 2020 due to the Covid-19 outbreak. The results are corroborated when employing other macro factors, whose predictive power for real GDP growth has been emphasised in the literature, such as the Institute for Supply Management (ISM), the Chicago FED National Activity Index (CFNAI) and the Conference Board Leading Indicator (CBLI), as well as when considering the slope of the yield curve.

Given the large economic implications associated to the Covid-19 disease, we also assess whether macroeconomic developments during the Spanish flu in 1918-1920 can provide some insights on the macroeconomic risk. By employing the mortality rates across countries due to the Spanish flu (i.e. 2% of the world's population) and World War I, we estimate the drop in real per capita GDP for the typical country to be 6.7% over the cumulated period 1918-1920 due to the pandemic outbreak, but we estimate that the expected per capita GDP growth rate could have plummeted by 11.4% in case of contraction. Although the mortality rate due to the Covid-19 pandemic will be much lower, due to the health infrastructure, the stringent lockdown measures and the general knowledge about the disease, the insights from the Spanish flu should not be dismissed, as in both periods a large number of countries have adopted social distancing measures with important implications for economic activity. Insights from the Spanish flu are informative on the potential depth of the recession following the Covid-19 pandemic.

I Introduction

On March 2, 2020, the Federal Reserve Board (FED)

> "*noted that since mid-February when concerns about the spread of the coronavirus beyond China had begun to intensify, global risk asset prices and sovereign yields had declined sharply. US and global equity indexes were lower than at the time of the Committee's meeting in January and implied equity market volatility had risen to levels not seen since 2015. The deterioration in risk sentiment had also been reflected in a significant widening in US and European corporate credit spreads and in peripheral European spreads. Amid the ongoing market volatility, issuance of investment-grade and high-yield corporate bonds and of leveraged loans had generally dried up.*"[1]

On the same day, the Federal Open Market Committee (FOMC) has evaluated as strong the fundamentals of the US economy and, on March 3, has approved a 50 basis points decrease in the primary credit rate, uniquely focusing on the information from financial markets, as the coronavirus posed evolving risks to economic activity.[2]

The analysis of downside risks to economic growth is central in real-time macroeconomic forecasting, because the weakening of economic activity can manifest itself in the higher moments of the distribution, even if the forecast of real GDP growth's conditional mean remains unchanged. Forecasting the higher moments is of paramount importance, because often policymakers justify a neutral monetary policy stance or conduct an expansionary monetary policy referring to risks to the economic activity titled to the downside.

This paper addresses the question whether financial variables can help predict in real-time macroeconomic risk once controlling for macroeconomic factors. The analysis is undertaken around the two biggest recession periods that the United States (US) phased after the Second World War: the Great Recession, which according to the NBER (US National Bureau of Economic Research) started in December 2007 and ended in June 2009, and the Covid-19 Recession in 2020, which according to the NBER started in February 2020. Both recessions were not foreseen by policymakers as well as the majority of academic and professional economists. Using real-time vintages, we show that financial variables forecast the Great Recession (first moment) and the associated macroeconomic risk (higher moments) already at the beginning of 2008. As for the Covid-19 Recession, though it was not expected in

[1] The FED staff also noted that "the spread of the virus was at an earlier stage in the United States and its effects were not yet visible in monthly economic indicators, although there had been some softening in daily sentiment indexes and travel-related transactions." https://www.federalreserve.gov/monetarypolicy/fomcminutes20200315.htm

[2] https://www.federalreserve.gov/monetarypolicy/files/monetary20200303a1.pdf

the US on March 15, 2020,[3] the same financial indicators forecast negative growth and a sharp downside in macroeconomic risk already in the first week of March, while established macroeconomic factors show the economic damage wrought by the coronavirus crisis only after the unprecedented drop of the US Markit flash Composite Purchasing Managers Index Output (henceforth, PMI) on March 24 and the fall in US nonfarm payroll by 701.000 in March released on April 3.[4] Against this background, the FED has cut its benchmark interest rate by 50 basis points on March 3, 2020, uniquely focusing on the information from financial markets, followed by an additional 100 basis points cut on March 15, 2020. Therefore, the results of this paper, obtained using real-time data, are comforting.

With regard to the Great Recession, the comparison of the results of the complete model with macro and financial factors vis-à-vis a model with macro factors only, already with data for the third quarter of 2007 (e.g. December 2007 data vintage), suggests that in 2007Q4 (i) the conditional probability density obtained with models including financial variables is more skewed to the left, (ii) the expected value of GDP growth is quarter-on-quarter (q-o-q) 0.4 percentage points lower, (iii) the probability of a contraction in economic activity is 34% and the expected value of GDP growth in case of a contraction amounts to -0.86% q-o-q, twice the figures suggested by the model with macro variables only, (iv) the 5% expected shortfall, which measures the expected GDP growth rate in the lower 5% tail of the conditional probability density, is three times as large, and (v) the downside entropy, which measures the conditional risks to the downside in excess of the downside risks predicted by the unconditional distribution (see Adrian et al., 2019), is twice as large. More adverse results are obtained over the subsequent quarters well before the Lehman Brothers' collapse and similar inferences apply when forecasting macroeconomic risk one-year ahead.

Similar implications can be drawn carrying out the analysis in real time in 2020Q1, when predicting macroeconomic risk associated to the Covid-19 Recession. The conditional probability densities one-quarter and one-year ahead with the full model including financial variables are less left-skewed than a model with macro variables only until February 21, 2020. However, since then, due to sharp increases in risk premia and uncertainty, the densities obtained with a model including financial variables have started to shift to the left daily and

[3] The OECD interim economic outlook released on March 2, 2020 forecasted US GDP growth at 1.9% in 2020, -0.1% revision relative to the November 2019 issue. The world recession appears only once in the Minutes of the Federal Open Market Committee held on March, 15 associated to a more adverse scenario. Members of the Committee have judged that the effects of the coronavirus would weigh on economic activity in the near term and pose risks to the economic outlook. On the same day, the US Treasury Secretary Steven Mnuchin said that he was not expecting a recession.

[4] A weekly US economic activity index developed during the coronavirus crisis by the FED indicate a fall in US economic activity on March 21 (Lewis et al., 2020). The Weekly Economic Index is available from January 2008. The number of observations is insufficient to estimate the non-linear model of our paper.

have become more skewed; thereby, pointing to higher risk of recession than a model with macro factors only. These results remain valid even when the flash release of the sharp drop in the PMI was published on March 24. The full model with financial variables expects negative GDP growth already before the second monetary policy intervention by the FED, while the model with macro variables only would still suggest positive growth. The probability of contraction with the full model jumps from 12% on February 21 to 54% on March 13 and increases further to 90% on March 24, when the prediction of the GDP growth based on the mean or the median for 2020Q1 becomes very accurate. The model with the macro factor only provides similar output contractions only with the April flash PMI release on April 23, more than six weeks later the information provided by financial markets. In these six weeks, fiscal, monetary and supervisory authorities have taken important policy decisions to safeguard economic activity, calm financial markets and, thereby, reduce dramatically the risks of adverse macro-financial feedback loops. The Covid-19 recession is truly an unexpected event. Financial variables have served policymakers early in March 2020, providing timely warnings about the severity of the crisis and the macroeconomic risk involved.

We employ key specific macro and financial variables, which are typically and widely used in the profession. The main analysis is carried out employing the IHS Markit US Composite PMI, the US Composite Indicator of Systemic Stress (CISS), which is an aggregation of indicators in a broad range of financial market segments capturing financial stress,[5] and corporate spreads of investment grade bonds issued by US non-financial corporations, which we construct following the method suggested by Gilchrist and Zakrajšek (2012). The advantage of the PMI is that its flash estimates are available already 7-10 days before the end of the current month and, as a result, it is the first major survey-based macroeconomic indicator to provide evidence of a sharp drop in economic activity globally in March 2020 due to the Covid-19 outbreak. The results are corroborated when employing other macro factors, whose predictive power for real GDP growth has been emphasised in the literature.

We address our key question of the paper using quantile regressions and the flexible skewed t-distribution, which is indexed over four parameters that trace the mean, variance, skewness and kurtosis of the distribution. We extend the univariate case (i.e. the National Financial Condition Index (NFCI) in the case of Adrian et al., 2019) to the multivariate setting with macro and financial variables.[6]

[5] The US CISS is also used in a recent note by the FED to assess the implications of Covid-19 (https://libertystreeteconomics.newyorkfed.org/2020/05/what-do-financial-conditions-tell-us-about-risks-to-gdp-growth.html). The correspondent CISS indicator for the euro area is informative to forecast tail risks in economic activity (Figueres and Jarociński, 2020; Chavleishvili and Manganelli, 2019).

[6] We do not use the NFCI in this paper primarily because real time data for this indicator are only available for the recent past. Moreover, it is compiled using also macro variables, such as credit and leverage.

Given the uncertainty surrounding the economic implications due to the Covid-19 disease, we complement the analysis by getting insights from the macroeconomic risk due to the Spanish flu in 1918-1920, by employing the mortality rates across countries due to the Spanish flu and World War I (Barro et al., 2020). Insights from the Spanish flu are informative on the potential depth of the recession following the Covid-19 pandemic.

A strand of the literature has found that financial variables display little predictability for the business cycle (e.g. Stock and Watson, 2003; Hatzius et al., 2010; Plagborg-Møller et al., 2020). Another strand of the literature has suggested that financial and credit conditions can lead economic outcome (e.g. Bloom, 2009; Matheson, 2012; Bekaert and Hoerova, 2014) and, particularly corporate credit spreads can lead the business cycle (Faust et al., 2013; López-Salido et al., 2017). Recent research has found that the relationship between financial conditions and the business cycle is non-linear and it emerges during crises/recessions (Giglio et al., 2016; Adrian et al., 2019; Brownlees and Souza, 2019; Adams et al., 2020). Specifically, Giglio et al. (2016) find that systemic risk predicts macroeconomic downturns. Our approach differs from Giglio et al. (2016) and Adrian et al. (2019), because we use a multivariate setting separating the macro variables from the financial variables in real time, with each time series being indexed by the date when it becomes available to the public.

The remaining sections of the paper are structured as follows: Section II presents the data to motivate the analysis of the paper. Section III describes briefly the econometric approach and discusses the empirical results. Section IV investigates the role of other macro-economic and financial variables. Section V concludes.

II Data and Facts

This section presents data and stylised facts. Given the data availability on corporate spreads and the financial stress indicator, the time-series analysis for the US is carried out from 1973Q1 to 2019Q4, which resembles the sample period employed by Adrian et al. (2019). All the econometric analysis of the paper is carried out using real-time data.

II.A Real GDP Growth

Figure 1 shows the actual and the fitted distributions of US real GDP growth over the samples 1973Q1-2019Q4 (blue) and 2007Q4-2019Q4 (red) used in this paper. GDP growth is characterized by skewness and fat tails, and its distribution in the shorter and most recent sample is slightly shifted to the left and leptokurtic. Therefore, the non-linear approach may better fit the skewed and fat-tailed nature of the distribution of GDP growth.

II.B Macro Factors

The key macro factor for the analysis is the Composite PMI Output. PMI data are used by policymakers, financial and corporate professionals to better understand where economies are headed, as they provide accurate and timely insight into the health of an economy. The monthly data are derived from surveys by polling businesses. The producers of US PMIs are the ISM,[7] which originated its manufacturing metric for the United States since 1948, and the IHS Markit Group, which produces metrics based on ISM's work for about 40 countries worldwide. The IHS Markit PMI dataset is compiled from a survey panel of senior executives at private sector companies.

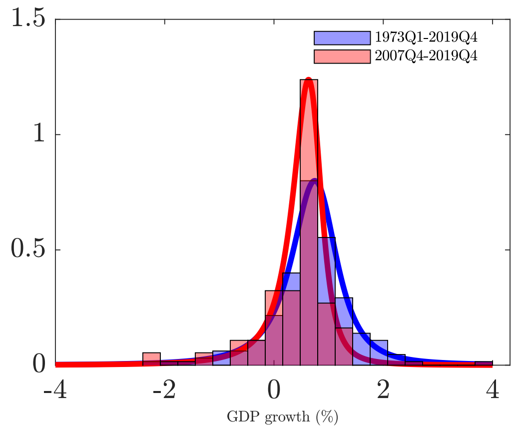
PMIs are calculated as diffusion indices. For each variable, the index is the sum of the percentage of 'higher' responses and half the percentage of 'no change' responses. The indices vary between 0 and 100, with a reading above 50 indicating an overall increase compared to the previous month (e.g. economic expansion), and below 50 an overall decrease (e.g. economic contraction). The indices are seasonally adjusted.

The comparison between PMIs and real GDP growth show a clear, tight link (see Panels A and B of Figure 2). The contemporaneous correlation over the period 1997Q3-2019Q4 with Markit PMI is 72%,[8] while the correlation with the Manufacturing ISM is 53%. PMIs lead

[7]The ISM was known as the National Association of Purchasing Management (NAPM) until January 2, 2002.

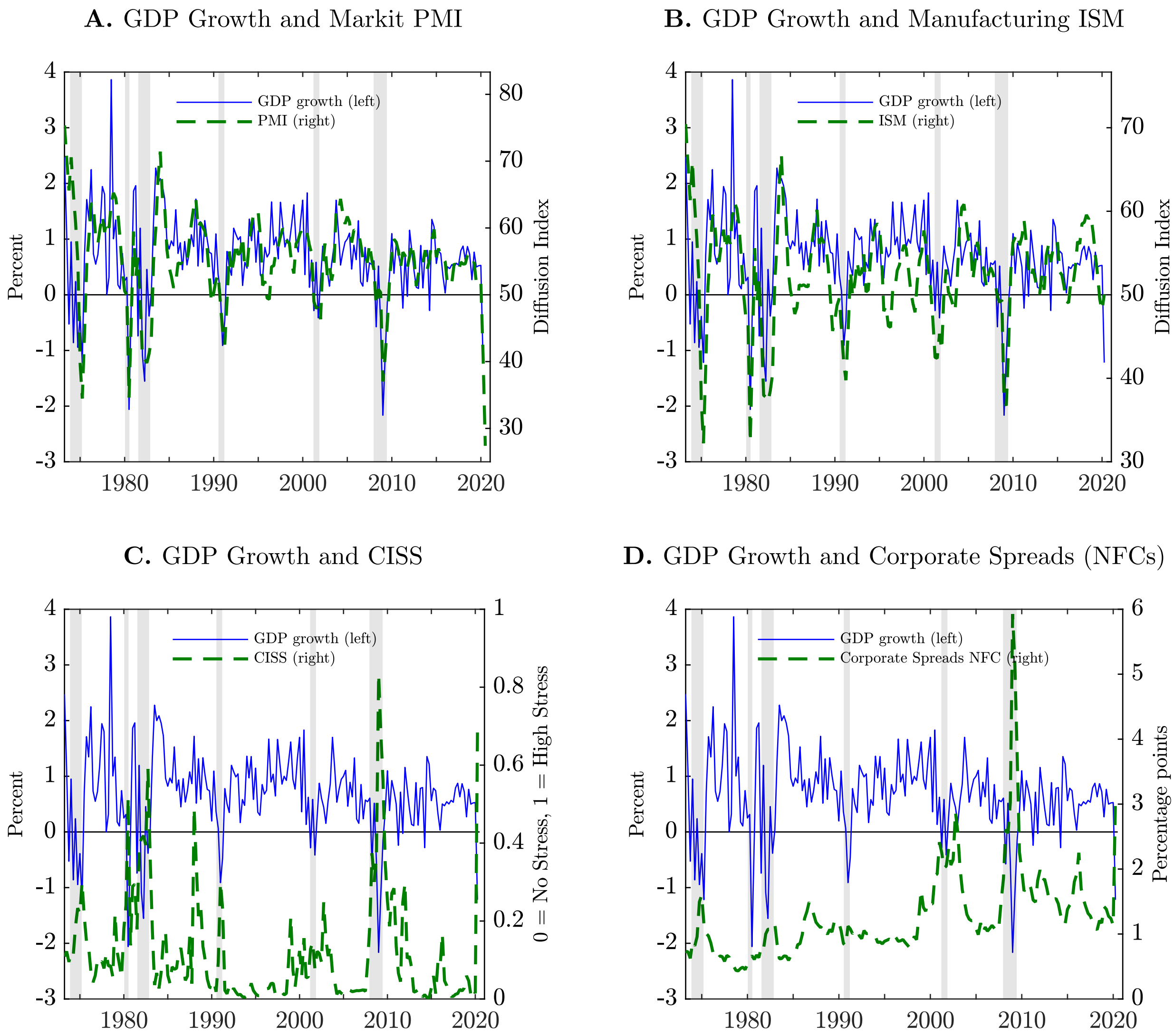
[8]The IHS Markit produces its PMI data from 2007 and extends back the time series to 1997 using the information from the manufacturing and non-manufacturing ISM. Given that the quarterly correlation between 2007 and 2019 among Manufacturing ISM and Markit PMIs is 82%, we chain the time series from 1997 backwards with the Manufacturing ISM.

Figure 1: Real GDP growth (Quarter-on-quarter, %)



Sources: FRED-QD and authors' calculations.
Notes: The histograms provide the actual quarter-on-quarter real GDP growth in percent over the samples 1973Q1-2019Q4 and 2007Q4-2019Q4. The fitted distributions are computed using the skewed t-distributions developed by Azzalini and Capitanio (2003) and parameters are estimated following Adrian et al. (2019).

Figure 2: Macro Factors, Financial Factors and Real GDP Growth



Sources: ECB, FRED, IHS Markit, ISM, Merrill Lynch and authors' calculations.
Notes: The IHS Markit PMI Composite Output is chained from 1997 backwards with the Manufacturing ISM. Corporate spreads are constructed by subtracting from the yield-to-maturity of each bond the Treasury yield of a similar duration. Data are computed as quarterly averages except for 2020Q1, where the charts show the March outturns for PMI and ISM and the March 24 outturns for CISS and corporate spreads. Shaded areas indicate NBER-recession periods. Sample period: 1973Q1-2020Q1.

real GDP growth. The quarterly cross correlation with a one-period lead is high, amounting to 45% for Markit PMI, but somewhat smaller for Manufacturing ISM (35%). The Markit PMI has plummeted to 41 in March 2020, down from 49.6 one month earlier, while the Manufacturing ISM has declined mildly to 49.1, just below the contractionary threshold, compared to 50.1 one month earlier.[9]

[9]The contemporaneous correlation over the period 1997Q3-2019Q4 between real GDP growth and manufacturing and non-manufacturing ISM is 62% and the one-period lead correlation is 36%. The manufacturing and non-manufacturing ISM has remained in expansionary territory in March 2020, declining to 52.1 com-

The fall in real GDP growth by 5.1% q-o-q annualised in 2020Q1 is more in line with the prediction from the Markit PMI.

The additional advantage of the Markit PMI is that its flash estimates are available already about 7-10 days before the end of the current month, while the Manufacturing ISM is available at the beginning of the subsequent month. Being timelier, it is very closely monitored by policymakers and financial markets. The flash PMI for the US is available since 2009 and it is the first major survey indicator to provide evidence on March 24, 2020 of a sharp drop in economic activity, both in the US and globally, due to the Covid-19 outbreak.

We compare the results employing other macro variables typically used in the literature and reported by the media, such as the ISM, the CFNAI and the CBLI in Section IV.

II.C Composite Indicator of Systemic Stress

The CISS for the United States is an aggregation of 15 indicators capturing financial stress symptoms. All indicators are first transformed and thereby homogenized based on their empirical cumulative distribution function (probability integral transform). System-wide stress is then computed by weighing each pair of transformed indicators by its time-varying correlation coefficient (computed as exponentially weighted moving averages) in strict analogy to standard portfolio-theoretic principles. This methodology allows the CISS to put relatively more weight on situations in which stress prevails in several market segments at the same time, consistent with the idea that only widespread and thus systemic financial stress severely endangers the smooth provision of financial services to the real economy. All transformations are carried out using recursion methods from 2002 onward. Therefore, the CISS is a real-time indicator, as each point in time from 2002 is based on historical data.

The CISS is measured using indicators from (i) the money markets, such as the volatility of 3-month Commercial Paper Nonfinancial (AA-rated) rate, the Ted spread (rate differential between the 3-month LIBOR and the Treasury bill rates), and the rate differential between 3-month commercial paper and the Treasury bill rates; (ii) the bond markets, such as return volatility of the 10-year Treasury bond, the 10-year yield differential between AAA-rated corporate bonds and Treasury bonds, and the 10-year yield differential between BAA- and AAA-rated corporate bonds; (iii) the equity markets, such as the return volatilities, book-to-price ratios and cumulated maximum percentage index losses over a 2-year moving window separately for non-financial and financial corporations; and (iv) the foreign exchange markets, such as return volatility of the US Dollar exchange rate vis-à-vis the Euro, the Japanese Yen, and the Canadian Dollar. Its source is the European Central Bank (see also Kremer et al.,

pared to 56.5 one month earlier.

2012).

Panel C of Figure 2 shows the relationship between real GDP growth and the CISS indicator ranging between zero (no stress) and 1 (high stress). The CISS rises at the beginning of NBER recessions. Specifically, in the case of the Great Recession, the CISS started to rise already since July 2007. Similarly for the Covid-19 recession, the CISS started to rise at the end of February 2020, skyrocketed in the first two weeks of March and peaked at the end of March, suggesting a sharp slowdown in economic activity. The US VIX, a key measure of equity market volatility, and the OFR (Office Financial Research) Financial Stress Index for the US, a gauge of systemic financial stress, are highly correlated with the CISS and are a potential alternative to the CISS. However, the US VIX starts from January 1990, while the OFR Financial Stress Index starts only in January 2000.

II.D Corporate Bond Spreads

Corporate spreads are constructed following the approach suggested by Gilchrist and Zakrajšek (2012). Specifically, we use individual security level data to construct duration adjusted security-specific credit spreads. They are compiled using the individual bond data of Bank of America Merrill Lynch (BofAML), which is part of Intercontinental Exchange (NYSE: ICE), an operator of global exchanges and clearing houses which includes the New York Stock Exchange (NYSE). The outstanding amount of corporate bonds in the BofAML database issued in US dollars is about 9 trillions of which 6 trillion issued in the US.

The data cover investment grade and high yield corporate debt publicly issued in the major markets. Qualifying securities must satisfy the following requirements to be included: (i) a minimum size requirement of US dollar (USD) 250 million, (ii) a rating issued by Moody's, S&P or Fitch, (iii) a fixed coupon schedule, and (iv) a minimum 18 month maturity at issuance.

We collect data at monthly frequency, more precisely on the last Friday of the month. This avoids potential statistical biases resulting from the rebalancing of constituents on the last calendar day of the month.[10] We retain bonds with a residual maturity above 11 months that are available for at least two consecutive months and are issued by companies whose "country of risk" is based in the US and are issued in USD.[11] Bond prices are based on

[10]The BofAML constituents are rebalanced on the last calendar day of the month, based on information available up to and including the third business day before the last business day of the month. Bond issues that meet the qualifying criteria are included in the BofAML constituents for the following month. Issues that no longer meet the criteria during the course of the month remain in the BofAML data set until the next month-end rebalancing, at which point they are removed.

[11]The country of risk is based on the physical location of the issuer's operating headquarters with the following exceptions: (i) holding company issuers are assigned a country of risk based on the location of the majority of operating assets. If no single country represents a majority of operating assets, or if this cannot

quotes, not transaction prices.

We focus on the investment grade rating class issued by non-financial corporations, because movements in this asset class are more informative, being less volatile. Specifically, for each security j, the credit spread $s_{j,t}[k]$ is constructed by subtracting from the yield to maturity, $R_{j,t}[k]$, the Treasury yield curve of a similar duration k, $i_t[k]$,[12]

$$s_{j,t}[k] = R_{j,t}[k] - i_t[k]$$

and the corporate bond spread index is a simple average:

$$\overline{s}_t[k] = \frac{1}{N_t} \sum_j \left(s_{j,t}[k] \right),$$

where N_t is the total number of bonds at time t.

The BofAML database is available since January 1997. Corporate bond spreads for previous years are chained back using the index provided by Gilchrist and Zakrajšek (2012).

Panel D of Figure 2 shows the relation between US corporate bond spreads and real GDP growth. Corporate bond spreads start to rise before the beginning of recessions, as identified by the NBER. This is rather clear in the case of the Great Recession, as corporate bond spreads started to rise already since July 2007, as highlighted by Gilchrist and Zakrajšek (2012). As we have already shown for the CISS, corporate spreads started to rise at the end of February 2020, skyrocketed in the first two weeks of March and peaked at the end of March, as investors demand a higher risk premium to purchase bonds, a feature of economic downturns.

III Predicting Macroeconomic Risk in Real Time

III.A The Quantile Regression and the Skewed t-Distribution

The real-time assessment of macroeconomic risk draws on the two-step semiparametrical approach as in Adrian et al. (2019). The first step of this methodology corresponds to a prediction exercise for GDP growth. More precisely, macroeconomic risk can be assessed by casting a predictive model for GDP growth in the quantile regression framework of Koenker

be determined, the country of risk is the issuer's operating headquarters; (ii) bank branch issues are assigned the country of risk of the parent entity.

[12]The Treasury yield curve is provided by the FED (https://www.federalreserve.gov/data/yield-curve-tables/feds200628_1.html) and is constructed using the method by Gürkaynak et al. (2007).

and Bassett (1978).[13] For each vintage Ω_v, we use the quarterly average of the regressors for quarters different from the forecast period, whereas the most recent data point needed for the out-of-sample forecast is the latest outturn of the series, including the flash releases. The forecast of GDP growth exploits the relation between y_{t+h} and the vector $x^i_{t+1|\Omega_v}$ containing the predictors given the information set Ω available on a specific data release v. We focus the analysis on horizon $h \in \{1, 4\}$. When $h = 1$, the assessment of macroeconomic risk is based on a real-time out-of-sample nowcast of GDP growth (Giannone et al., 2008; Altissimo et al., 2010; Banbura et al., 2013); instead, when $h = 4$, the prediction exercise corresponds to a real-time out-of-sample forecast of the year-on-year quarterly real GDP growth, $y_{t+4} = \frac{1}{4}\sum_{h=1}^{4} y_{t+h}$. We model the different quantiles of GDP growth's conditional distribution independently by estimating

$$\hat{\beta}^{i,h}_{\tau} = \underset{\beta^{i,h}_{\tau}}{argmin} \sum_{t=1}^{T-h} \Big(\tau \cdot \mathbb{1}_{(y^i_{t+h} \geq x^i_{t+1|\Omega_v}\beta^{i,h}_{\tau})} \mid y^i_{t+h} - x^i_{t+1|\Omega_v}\beta^{i,h}_{\tau} \mid \\ + (1-\tau) \cdot \mathbb{1}_{(y^i_{t+h} < x^i_{t+1|\Omega_v}\beta^{i,h}_{\tau})} \mid y^i_{t+h} - x^i_{t+1|\Omega_v}\beta^{i,h}_{\tau} \mid \Big)$$

where i denotes the model and $\mathbb{1}_{(\cdot)}$ the indicator function. Quantiles of the conditional distribution of GDP growth are expressed as linear functions ($\hat{\beta}^{i,h}_{\tau}$) of observed covariates. The predicted values from these quantile regressions, $\hat{Q}^i_{y_{t+h}|x^i_{t+1|\Omega_v}}(\tau \mid x^i_{t+1|\Omega_v}) = x^i_{t+1|\Omega_v}\hat{\beta}^{i,h}_{\tau}$, correspond to the quantiles τ of the predictive distribution of y^i_{t+h} conditional on $x^i_{t+1|\Omega_v}$. This non-linear approach acknowledges the skewed and fat-tailed nature of GDP growth, which is documented in, e.g., Fagiolo et al. (2008), Williams et al. (2017), Atalay et al. (2018), Bloom et al. (2018), Adrian et al. (2019), Salgado et al. (2019), Loria et al. (2019), Carriero et al. (2020) and Plagborg-Møller et al. (2020). Moreover, the use of the conditional quantile function facilitates the evaluation of macroeconomic risk reflected by the lower percentiles of the quantile function of GDP growth: a fall in the lower percentiles of the conditional distribution of GDP growth indicates an increase in macroeconomic risk. Finally, the predictive power of the conditioning variables most likely exhibits substantial heterogeneity across percentiles of GDP growth distribution, which may be particularly true for financial variables in predicting the left tail of the distribution, as illustrated by, e.g., Giglio et al. (2016), Adrian et al. (2018), Adrian et al. (2019), Beutel et al. (2019), Loria et al. (2019), Chavleishvili and Manganelli (2019), Figueres and Jarociński (2020),

In the second step, the predictive conditional quantile function is smoothed into an inverse cumulative skewed t-distribution (Azzalini and Capitanio, 2003) by fitting the 5th, 25th,

[13] A variety of quantile regression applications can be found in Buchinsky (1994), Koenker and Hallock (2001), Engle and Manganelli (2004), Koenker (2005), White et al. (2015), Koenker (2017), Kiley (2018), Escanciano and Hualde (2020), Griffin and Mitrodima (2020) and Song and Taamouti (2020).

75th and 95th quantiles of the resulting probability density to their respective counterparts estimated by the quantile regression. This allows us to map the predictive conditional quantiles into a predictive conditional probability density function, which facilitates the computation of a number of additional statistics such as the probability of a contraction in economic activity, the expected severity of such a contraction, and other measures that characterize the left-tail of the predictive distribution, such as the downside entropy and the 5% expected shortfall. These statistics require the integration of a probability density function. In particular, we use a skewed t-distribution that is governed by four parameters (μ, σ, α, ν) that relate to the location, scale, shape, and mean of the distribution. μ, σ, α and ν are chosen for each quarter at $t+h$ to solve the minimization problem

$$\{\hat{\mu}_{t+h}, \hat{\sigma}_{t+h}, \hat{\alpha}_{t+h}, \hat{\nu}_{t+h}\} = \underset{\mu,\sigma,\alpha,\nu}{argmin} \sum_{\tau} \left(\hat{Q}^{i}_{y_{t+h}|x^{i}_{t+1|\Omega_v}} (\tau \mid x^{i}_{t+1|\Omega_v}) - F^{-1}\left(\tau; \mu, \sigma, \alpha, \nu\right) \right)^2,$$

where $\hat{\mu}_{t+h} \in$, $\hat{\sigma}_{t+h} \in^{+}$, $\hat{\alpha}_{t+h} \in$, $\hat{\nu}_{t+h} \in^{+}$, F is the cumulative probability distribution function of the skewed t-distribution developed by Azzalini and Capitanio (2003) and f is the associated probability density function. The skewed t-distribution is a natural choice to model the predictive distribution for GDP growth, since it can flexibly introduce skewness and kurtosis, while retaining symmetric and normal-tailed probability densities as special cases.[14]

The estimated probability density of the skewed t-distribution of y_{t+h} can be interpreted as a density forecast for GDP growth and is given by:

$$\hat{\mathcal{F}}^{i}_{t+h,\Omega_\nu}(y) := \hat{f}^{i}_{y_{t+h}|x^{i}_{t+1|\Omega_v}}(y \mid x^{i}_{t+1|\Omega_v}) = f(y; \hat{\mu}_{t+h}, \hat{\sigma}_{t+h}, \hat{\alpha}_{t+h}, \hat{\nu}_{t+h}).$$

Similarly, the unconditional distribution of GDP growth can be represented by

$$\hat{\mathcal{G}}_{t+h}(y) := \hat{g}^{i}_{y_{t+h}}(y) = f(y; \hat{\mu}^{u}_{t+h}, \hat{\sigma}^{u}_{t+h}, \hat{\alpha}^{u}_{t+h}, \hat{\nu}^{u}_{t+h}).$$

Both distributions are used to derive summary metrics. Following Adrian et al. (2019), we compute the 5% expected shortfall and the upside and downside entropy as measures to assess the tail behavior of the predictive distribution for GDP growth. Entropy is defined relative to the unconditional distribution of GDP growth, and measures the extent to which the upside or downside risks, in the highest or lowest 50% of the conditional distribution

[14] Ganics et al. (2020) confirm that the more flexible skewed t-distribution appears to fit better during the Great Recession.

outweigh the upside or downside risks of the unconditional distribution:

$$\mathcal{L}^D_{t+h}\left(\hat{\mathcal{F}}^i_{t+h,\Omega_\nu};\hat{\mathcal{G}}_{t+h}\right) = -\int_{-\infty}^{\hat{F}^{-1}_{y_{t+h}}(0.5)}\left(log\ \hat{\mathcal{G}}_{t+h}(y) - log\ \hat{\mathcal{F}}^i_{t+h,\Omega_\nu}(y)\right)\hat{\mathcal{F}}^i_{t+h,\Omega_\nu}(y)dy,$$
$$\mathcal{L}^U_{t+h}\left(\hat{\mathcal{F}}^i_{t+h,\Omega_\nu};\hat{\mathcal{G}}_{t+h}\right) = -\int_{\hat{F}^{-1}_{y_{t+h}}(0.5)}^{\infty}\left(log\ \hat{\mathcal{G}}_{t+h}(y) - log\ \hat{\mathcal{F}}^i_{t+h,\Omega_\nu}(y)\right)\hat{\mathcal{F}}^i_{t+h,\Omega_\nu}(y)dy.$$

where $\hat{F}_{y_{t+h}}(y)$ is the cumulative distribution associated with $\hat{\mathcal{F}}^i_{t+h,\Omega_\nu}(y)$. The expected shortfall is defined for a given probability π, say 5%, and gives the expected value of GDP growth in the 5% left tail of the predictive distribution:

$$SF_{t+h}(\pi) = \frac{1}{\pi}\int_0^\pi \hat{F}^{-1}_{y_{t+h}}\left(\tau;\hat{\mu}_{t+h},\hat{\sigma}_{t+h},\hat{\alpha}_{t+h},\hat{\nu}_{t+h}\right)d\tau.$$

We complement these metrics with two additional computations: the probability of a contraction in economic activity, defined as $\mathcal{P}_{0,t+h} = \hat{F}_{y_{t+h}}(0;\hat{\mu}_{t+h},\hat{\sigma}_{t+h},\hat{\alpha}_{t+h},\hat{\nu}_{t+h})$, and the associated expected value of economic growth conditional on a contraction, $SF_{t+h}(\mathcal{P}_{0,t+h})$.

We estimate the real-time distribution of real GDP growth conditioning on three different sets of variables. The most parsimonious model includes only the lag of q-o-q real GDP growth and a constant; then we add a timely macro variable that captures real economic activity, Markit PMI for our benchmark results; and finally we incorporate financial information by including either or both the CISS and the corporate spread of investment grade bonds of non-financial corporations. This set-up delivers four different models $i \in \{1,2,3,4\}$ with an increasing degree of completeness, and the most complete model that includes lagged growth, PMI and both financial variables will be referred to as “the full model”.

The relevance of the analysis is maximized by using real-time data, where we exploit the monthly frequency of the macro factors and the daily frequency of the financial factors. In that vein, we take the position of the policy-maker during the Great Recession and the Covid-19 Recession by using the real-time vintages of GDP and taking into account the various degrees of timeliness associated with the different variables in our models. Correspondingly, our data exhibits ragged-edges due to the very timely nature of the financial and macro variables used. As such, we quantify the macroeconomic risk using exclusively the information available to the policy-maker at a specific date.

III.B Quantifying the Macro Risk during the Great Recession

III.B.1 Skewed t-Distribution, Probability Density and Model Performance

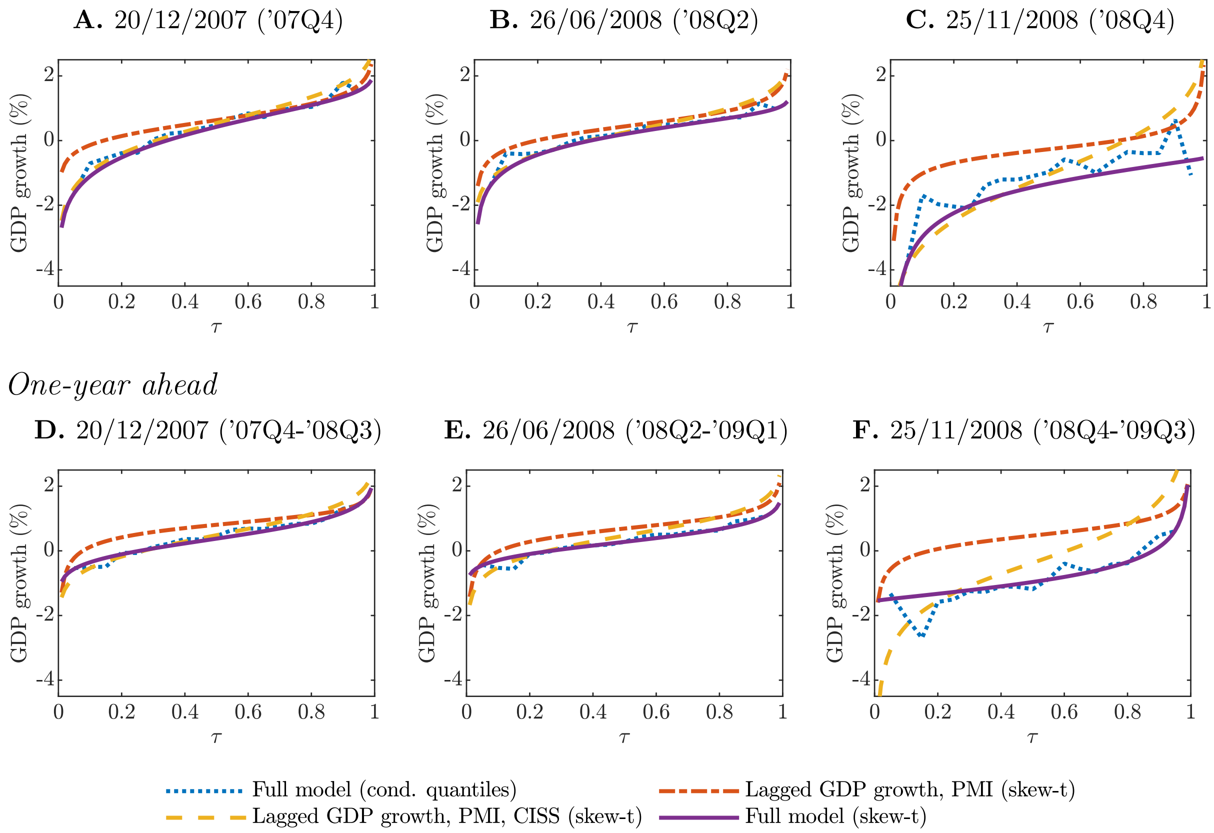
Figure 3 plots the estimated conditional quantile function of the full model and three versions of the fitted inverse cumulative skewed t-distribution, one conditional on PMI and lagged GDP growth, one conditional on CISS, PMI and lagged GDP growth and one that conditions on the complete model, for three sample dates during the Great Recession starting from the beginning of the recession in 2007Q4, a vintage before Lehman Brothers' bankruptcy (June 26, 2008) and when the FED announced the Large-Scale Asset Purchase (LSAP) programme (November 25, 2008). In all cases, the skewed t-distribution is sufficiently flexible to smooth the estimated quantile function associated to the full model, passing through all quantiles for both the one-quarter ahead and the one-year ahead forecasts. Figure 3 also shows that the distributions conditional on the macro variable only are always above the distributions conditional on both macro and financial variables. This suggests that financial variables pointed to downside risks to economic activity already in 2007Q4, a risk which became very strong in November 2008, precisely when the LSAP decision was announced.

Figure 4 shows the four versions of the fitted conditional probability density functions of GDP growth for all six vintages between 2007Q4 and 2009Q1. The comparison of the results indicates that the model with the macro factor only is characterized by a density function to the left of the one estimated by a model using only lagged GDP growth. Thereby, it provides useful information in real time. However, the models that also include financial variables are heavily left-skewed and hence signal higher GDP growth at risk already in 2007Q4, especially for the one-quarter ahead prediction. The model that includes only the CISS as a financial variable strongly reflects the large amount of uncertainty around future economic growth. However, the full model including corporate spreads tends to be more skewed to the left, which suggests that the full model is more informative during the beginning of a recession.

The mean and the median of GDP growth one-quarter and one-year ahead predicted during the Great Recession are much smaller when including the financial variables (see Table 1). In 2007Q4, the expected value of real GDP growth with the full model is 0.4 percentage points lower than the model with the macro factor only. The distribution conditional on the full model forecasts negative GDP growth already for 2008Q1, pointing to an economic contraction long before any other model. A contraction is predicted by the model with the macro factor only after the Lehman Brothers' bankruptcy in November 2008.

The comparison of the model predictions with the actual real-time GDP growth is informative also to understand the difficult role played by the policymakers. Each panel of Figure 4 contains two vertical lines: the bold line shows the final revised GDP growth,

Figure 3: Great Recession - Quantiles and Skewed t-Distribution of GDP growth

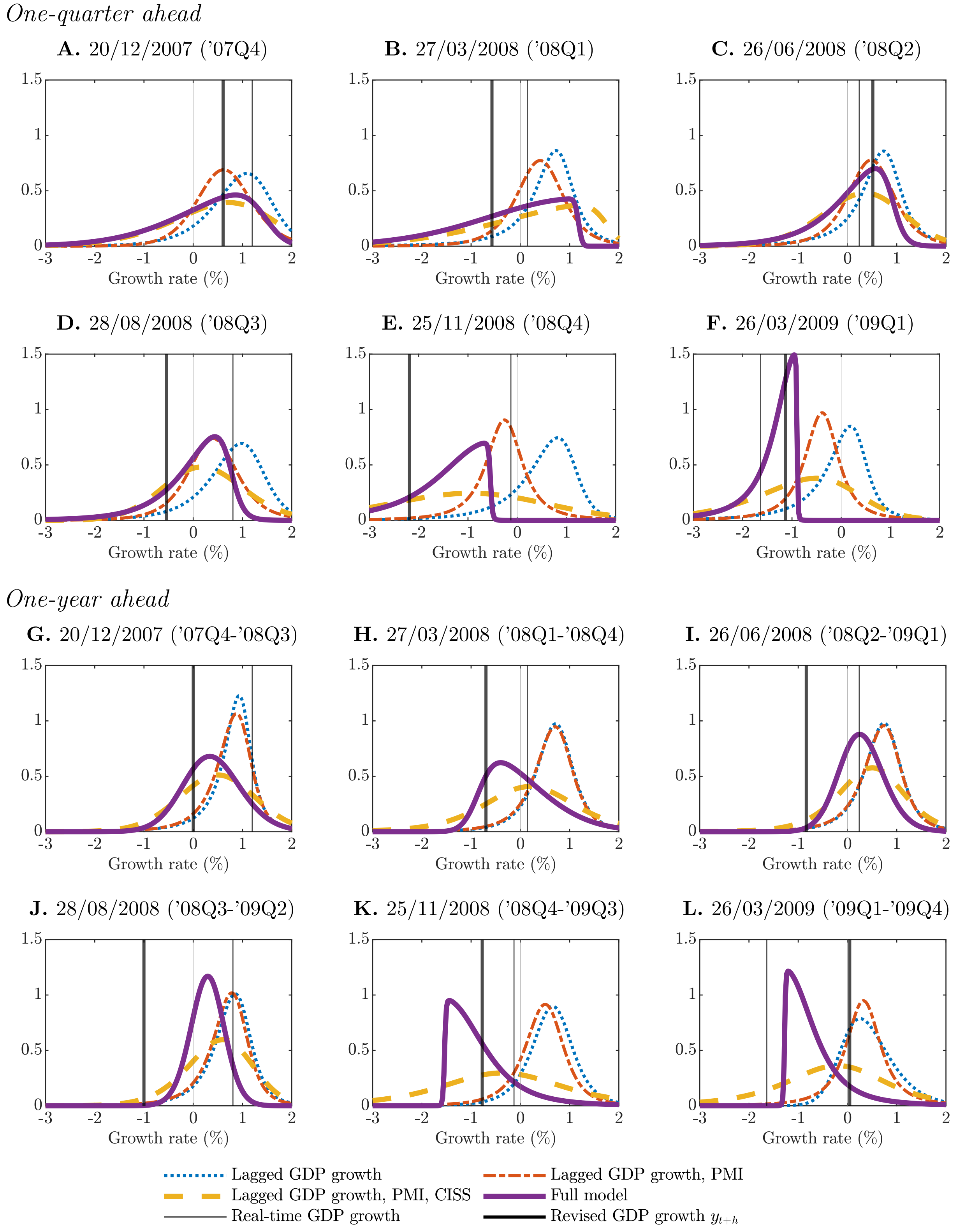


Notes: The panels in this figure show the conditional quantiles and the skewed-t inverse cumulative distribution functions for one-quarter ahead and one-year ahead real GDP growth of the 'Full model' including lagged GDP growth, PMI, CISS and corporate spreads. For comparison, we also report the skew t-inverse cumulative distribution functions obtained by fitting the quantiles obtained by conditioning only on lagged GDP and PMI as well as on lagged GDP growth, PMI and CISS. Three vintages are shown on 20 December 2007, 26 June 2008 and 25 November 2008. GDP growth one-year ahead is defined as $y_{t+4} = \frac{1}{4}\sum_{h=1}^{4} y_{t+h}$ (i.e. year-on-year quarterly real GDP growth).

which we aim to forecast at $t+h$, and the normal vertical line shows the real-time GDP growth available to the policymakers, which refers to the previous quarter. For example the GDP growth for 2008Q1 released on June 26, 2008 amounts to 0.24% q-o-q, which is higher than the previous quarter (0.14% q-o-q). Against this background, the FED in August 2008 "saw appreciable downside risk to growth" brought about by the stress in the financial and housing markets. At the same time, the FED was worried about the pass-through of higher energy and food prices into core inflation. Therefore, the FED directors even recommended a 25 basis point increase in the primary credit rate.[15] The final revised figure of real GDP

[15] In its monetary policy meeting on August 4, 2008, the FED "noted that stress in financial markets and the ongoing housing contraction were likely to damp economic growth further in the near term and saw appreciable downside risk to growth. However, they also noted that higher energy and food prices could pass through the core inflation measures. These directors concluded that the current stance of monetary policy achieved the appropriate balance between downside risk to growth and upside risk to inflation, and they preferred for

Figure 4: Great Recession - Probability Densities of GDP Growth



Notes: Each panel shows the skewed-t probability densities for four different models and the predictive quantiles for the full model. 'Full model' refers to the model that includes lagged GDP growth, PMI, CISS and corporate spreads of non-financial corporations. The title of each panel indicates the real-time date of the forecast and the predicted quarter(s). GDP growth one-year ahead is defined as $y_{t+4} = \frac{1}{4}\sum_{h=1}^{4} y_{t+h}$ (i.e. year-on-year quarterly real GDP growth).

growth for 2008Q1 released in subsequent years turned out to be strongly negative (-0.57% q-o-q). It is not unlikely that the policymakers would have intervened differently with the correct information. Strong economic growth was recorded in the subsequent quarter in 2008Q2 (0.81% q-o-q released on August 28, 2008 - see Panel D -, somewhat confirmed by the final revised 0.52% q-o-q outturn - see Panel C), just before Lehman Brothers' collapse in mid-September. At that time, despite the positive news on economic activity, the full model including financial variables continued to show densities strongly skewed to the left, pointing to higher GDP at risk. The GDP growth forecast one-year ahead is even more telling. The full model shows probability densities, which are clearly shifted to the left compared to the model with the macro factor only in the first four vintages before Lehman Brothers' collapse (i.e. Panels G-J). Hence, well before the Lehman Brothers' bankruptcy, the models including financial variables would have helped the policymakers to better address the forthcoming downside risk to economic growth. In concomitance with the LSAP announcement and thereafter, the models including financial variables forecasting one-year ahead show a right-skew distribution suggesting an increase in the upside risks (i.e. Panels K-L).

We evaluate the out-of-sample accuracy of the predictions by analyzing the mean squared forecast error (MSFE) and the predictive score. The latter evaluates the predictive distribution generated by a model at the realized value of the time series. Higher predictive scores indicate more accurate predictions because they show that outcomes considered more likely by the model are closer to the ex post realization. At the same time, a skewed density function might perform better in predicting the central tendency of the distribution, which implies lower prediction errors. Therefore, assessing the model performance based an both criteria is important. Table 1 compares the out-of-sample predictive scores of the predictive distribution conditional on macro and financial variables, as separated in the four different models. The predictive score for the distribution conditional on both macro and financial variables is above that of the distribution conditional only on macro factors four times out of six for the predictions one-quarter ahead and one-year ahead. Thus, the conditional distribution including financial variables is often more accurate, and rarely less accurate, than the one that conditions on macro factors only. Table 2 shows three measures of MSFE, defined as the average of the squared difference between the final revised data of GDP growth

now to monitor incoming information on the economy, financial markets, and inflation. Federal Reserve Bank directors recommending a 25-basis-point increase in the primary credit rate agreed that real economic activity continued to be soft and that financial markets had not yet fully stabilized. However, they cited indications that higher input costs were being passed through to product prices and that inflation expectations had risen and judged that the upside risks to inflation were of greater concern than the downside risks to growth. These directors concluded that an increase in the primary credit rate was appropriate in these circumstances." FED Press Release, "Minutes of Board discount rate meetings, July 7 through August 4, 2008", 2 September 2008, pg. 4. https://www.federalreserve.gov/newsevents/pressreleases/files/monetary20080902a1.pdf

Table 1: Great Recession - Out-of-Sample Accuracy of the Density Forecasts of GDP Growth

	One-quarter ahead						*One-year ahead*					
	07Q4	08Q1	08Q2	08Q3	08Q4	09Q1	08Q3	08Q4	09Q1	09Q2	09Q3	09Q4
Revised GDP growth[1]	0.61	-0.57	0.52	-0.54	-2.16	-1.12	0.00	-0.69	-0.83	-0.99	-0.77	0.05
Median												
GDP_{t-1}	0.98	0.64	0.65	0.86	0.63	0.04	0.87	0.69	0.70	0.79	0.64	0.38
GDP_{t-1}, PMI	0.63	0.39	0.47	0.39	-0.27	-0.41	0.81	0.66	0.69	0.72	0.47	0.32
GDP_{t-1}, PMI, CISS	0.54	0.37	0.30	0.21	-1.05	-0.74	0.49	0.18	0.47	0.53	-0.37	-0.27
Full model	0.42	-0.08	0.24	0.16	-1.34	-1.27	0.38	-0.09	0.28	0.29	-0.96	-0.82
Mean												
GDP_{t-1}	0.90	0.49	0.52	0.76	0.46	-0.18	0.76	0.65	0.66	0.72	0.62	0.44
GDP_{t-1}, PMI	0.64	0.37	0.46	0.39	-0.28	-0.46	0.73	0.61	0.64	0.65	0.43	0.32
GDP_{t-1}, PMI, CISS	0.45	0.11	0.27	0.23	-1.11	-0.88	0.48	0.18	0.45	0.49	-0.37	-0.32
Full model	0.25	-0.33	0.07	-0.01	-1.69	-1.55	0.40	0.04	0.29	0.28	-0.76	-0.62
Absolute Prediction Error w.r.t. Median of the Predictive Distribution												
GDP_{t-1}	0.37	1.21	0.14	1.40	2.82	1.17	0.87	1.38	1.54	1.79	1.41	0.33
GDP_{t-1}, PMI	0.03	0.96	0.04	0.94	1.92	0.72	0.81	1.36	1.53	1.72	1.25	0.28
GDP_{t-1}, PMI, CISS	0.07	0.95	0.21	0.75	1.14	0.39	0.48	0.88	1.31	1.53	0.40	0.31
Full model	0.18	0.50	0.27	0.70	0.85	0.14	0.38	0.61	1.11	1.29	0.19	0.87
Absolute Prediction Error w.r.t. Mean of the Predictive Distribution												
GDP_{t-1}	0.29	1.07	0.00	1.30	2.65	0.95	0.76	1.35	1.50	1.72	1.39	0.40
GDP_{t-1}, PMI	0.04	0.95	0.05	0.94	1.90	0.67	0.73	1.31	1.47	1.65	1.21	0.27
GDP_{t-1}, PMI, CISS	0.16	0.69	0.24	0.77	1.08	0.25	0.48	0.88	1.28	1.49	0.40	0.37
Full model	0.36	0.25	0.44	0.53	0.50	0.42	0.40	0.73	1.13	1.29	0.01	0.67
Predictive Score												
GDP_{t-1}	0.47	0.09	0.72	0.08	0.01	0.10	0.12	0.04	0.03	0.02	0.04	0.70
GDP_{t-1}, PMI	0.69	0.14	0.78	0.16	0.02	0.20	0.16	0.05	0.03	0.02	0.06	0.66
GDP_{t-1}, PMI, CISS	0.39	0.20	0.47	0.32	0.18	0.32	0.42	0.25	0.11	0.06	0.28	0.35
Full model	0.44	0.27	0.70	0.28	0.21	1.27	0.57	0.50	0.04	0.00	0.56	0.18

Notes: This table shows the median, the mean, the absolute prediction error and the predictive score. The absolute prediction error is defined as the absolute value of the difference between the revised data on GDP growth and the central tendency (mean or median) of the real-time predictive distributions of GDP growth. The predictive score is the predictive distribution evaluated at the realized value of GDP growth. Lower absolute prediction errors and higher predictive scores indicate more accurate predictions. ([1]) GDP growth one quarter ahead is measured as quarterly log difference, y_{t+1}. GDP growth one-year ahead is defined as $y_{t+4} = \frac{1}{4}\sum_{h=1}^{4} y_{t+h}$ (i.e. year-on-year quarterly real GDP growth).

and (i) the median, (ii) the mean and (iii) the mode of the real-time predictive distribution of GDP growth over the six vintages during the Great Recession. Our preferred central tendency measure is the mean, because the expected value takes into account the extreme values of the conditional distribution, which are very important to consider during economic contractions. The MSFE is the lowest by far for the models that include financial variables along all three dimensions corroborating the view that financial variables do help to forecast economic activity one-quarter ahead and one-year ahead. The better performance of the full model does not depend on a very good performance in one specific vintage. As shown in Table 1, the out-of-sample forecast error is smaller in the case of the full model relative to the model with the macro variable only in four out of six cases one-quarter ahead and five out of six cases one-year ahead. All in all, financial variables do help to forecast economic activity during the Great Recession.

Table 2: Great Recession - Mean Squared Forecast Errors

	One-quarter ahead			*One-year ahead*		
	Median	Mean	Mode	Median	Mean	Mode
GDP_{t-1}	2.16	1.80	2.52	1.72	1.61	1.82
GDP_{t-1}, PMI	1.00	0.98	1.02	1.57	1.45	1.69
GDP_{t-1}, PMI, CISS	0.49	0.40	0.93	0.89	0.86	0.94
Full model	0.26	0.18	0.97	0.70	0.68	0.84

Notes: This table shows the MSFE computed as the average of the squared difference between the revised data on GDP growth and (i) the median, (ii) the mean, and (iii) the mode of the real-time predictive distributions of GDP growth, using the six vintages of the Great Recession.

Table 3: Great Recession - Macroeconomic Risk

	One-quarter ahead						*One-year ahead*					
	07Q4	08Q1	08Q2	08Q3	08Q4	09Q1	08Q3	08Q4	09Q1	09Q2	09Q3	09Q4
5% Shortfall												
GDP_{t-1}	-0.99	-2.47	-2.40	-1.37	-2.20	-3.58	-1.36	-0.92	-0.93	-0.97	-0.78	-0.56
GDP_{t-1}, PMI	-0.76	-1.21	-1.11	-1.21	-2.51	-2.66	-0.91	-1.07	-1.04	-1.01	-1.23	-1.75
GDP_{t-1}, PMI, CISS	-2.08	-3.25	-1.63	-1.49	-4.82	-3.93	-1.21	-2.36	-1.37	-1.12	-4.35	-3.79
Full model	-2.28	-3.38	-2.12	-2.17	-5.58	-4.55	-0.80	-1.08	-0.63	-0.46	-1.52	-1.26
Upside Entropy												
GDP_{t-1}	0.19	-0.07	-0.06	0.10	-0.06	0.09	0.06	-0.11	-0.08	-0.01	-0.10	-0.17
GDP_{t-1}, PMI	-0.09	-0.13	-0.13	-0.15	0.24	0.42	-0.01	-0.13	-0.09	-0.07	-0.14	-0.09
GDP_{t-1}, PMI, CISS	-0.09	-0.14	-0.20	-0.21	-0.01	0.13	-0.14	-0.14	-0.17	-0.16	0.01	-0.09
Full model	-0.16	-0.12	-0.06	0.02	1.32	1.76	-0.19	-0.06	-0.11	0.06	0.65	0.62
Downside Entropy												
GDP_{t-1}	-0.11	0.12	0.09	-0.06	0.11	0.60	-0.05	0.17	0.11	0.01	0.14	0.50
GDP_{t-1}, PMI	0.17	0.37	0.29	0.36	0.93	1.00	0.02	0.19	0.12	0.08	0.33	0.49
GDP_{t-1}, PMI, CISS	0.27	0.45	0.47	0.56	1.37	1.14	0.47	0.78	0.42	0.35	1.43	1.12
Full model	0.36	0.75	0.49	0.56	1.47	1.47	0.59	1.12	0.67	0.67	2.10	1.91
Probability of Contraction												
GDP_{t-1}	10	16	16	13	20	47	7	10	9	8	11	21
GDP_{t-1}, PMI	14	24	20	24	72	82	8	11	10	10	17	24
GDP_{t-1}, PMI, CISS	31	39	36	40	74	77	27	43	26	23	61	60
Full model	34	53	37	41	100	100	26	55	27	20	88	88
Expected Value in case of Contraction												
GDP_{t-1}	-0.58	-0.99	-0.99	-0.69	-0.85	-0.82	-0.96	-0.54	-0.56	-0.62	-0.43	-0.25
GDP_{t-1}, PMI	-0.37	-0.46	-0.45	-0.46	-0.60	-0.67	-0.63	-0.57	-0.58	-0.60	-0.51	-0.57
GDP_{t-1}, PMI, CISS	-0.81	-1.19	-0.62	-0.58	-1.82	-1.30	-0.50	-0.82	-0.53	-0.47	-1.37	-1.16
Full model	-0.86	-1.17	-0.71	-0.69	-1.68	-1.53	-0.34	-0.49	-0.27	-0.21	-0.97	-0.83

Notes: This table summarises the macroeconomic risk in economic activity using five indicators. The 5% expected shortfall measures the expected value in the lower 5% tail of the conditional probability density. The downside entropy measures the conditional risks to the downside in excess of the downside risks predicted by the unconditional distribution, evaluated over the entire 50% left tail of the conditional distribution. The upside entropy measures the conditional risks to the upside in excess of the upside risks predicted by the unconditional distribution, evaluated over the entire 50% right tail of the conditional distribution. The probability of a contraction is the CDF evaluated at zero growth rate. The expected value in case of a contraction is the expected value conditional on a contraction. GDP growth one-year ahead is defined as $y_{t+4} = \frac{1}{4}\sum_{h=1}^{4} y_{t+h}$ (i.e. year-on-year quarterly real GDP growth).

III.B.2 Macro Risk Evaluation during the Great Recession

Entrepreneurs, investors and policymakers alike are often concerned with the downside and upside risks to the forecast. Particularly, if macroeconomic imbalances are building up or large adverse random shocks hit the economy, the quest for downside risk scenarios becomes impelling. We quantify the risk to GDP growth in real time during the Great Recession with a number of key statistics provided in Table 3.

First a measure that is often used in the literature is the 5% expected shortfall, which measures the expected value in the lower 5% tail of the conditional probability density. The 5% expected shortfall one-quarter ahead derived from the full model is always more negative than the corresponding figure in all other models for all six vintages during the Great Recession. The forecast one-quarter ahead, carried out with the 2007Q4 vintage and therefore with data up to 2007Q3, already indicates that the macro risk of the model including financial variables is three times larger. The macro risk rises in all models in the course of subsequent quarters. The macro risk estimated one-year ahead is also more accurate with the full model, because the downside risk rises while predicting year-on-year GDP growth up to 2009Q3 and then declines thereafter with the exit from the recession.

Another measure used to assess downside risk is the downside entropy proposed by Adrian et al. (2019), which measures the conditional risks to the downside in excess of the downside risks predicted by the unconditional distribution, evaluated over the entire 50% left tail of the conditional distribution. Notice that if both distributions are negatively skewed, downside entropy will be low, while the expected shortfall will be high. Table 3 shows that the full model is characterized by the largest downside entropy across all models, all vintages, one-quarter ahead and one-year ahead. For completeness, the table also reports the upside entropy, which focuses on the entire 50% right tail of the conditional distribution. It is interesting to point out that the full model provides the largest upside risk one-year ahead in 2009Q3 and 2009Q4, when the US economy exit the recession phase, while all other models still estimate a negative divergence between the conditional and the unconditional densities to the right of the distribution. Nevertheless, we should stress that the actual one-year ahead quarterly GDP growth based on final data is strongly negative in 2009Q3 (-0.77% q-o-q) and just above zero in 2009Q4 (0.05% q-o-q).

An alternative statistic, which we suggest here, is the probability of a contraction in economic activity. The probability that the predictive density attaches to negative economic growth is given by the cumulative distribution function (CDF) evaluated at a zero growth rate. The probability of a contraction one-quarter ahead estimated with the full model is the largest in all vintages and across all models. The probability of a contraction estimated for 2007Q4 is already 34%, about three times larger than the estimates provided by a model with the macro factor only. It ranges between 37% and 53% before Lehman Brothers' collapse, after that it reached 100%. The expected value of GDP growth conditional on a contraction is in line with actual outturns in real GDP growth from 2008Q3 onwards. We can safely conclude that financial variables do help forecast economic activity and evaluate macroeconomic risk during the Great Recession.

III.C Quantifying the Macro Risk during the Covid-19 Recession

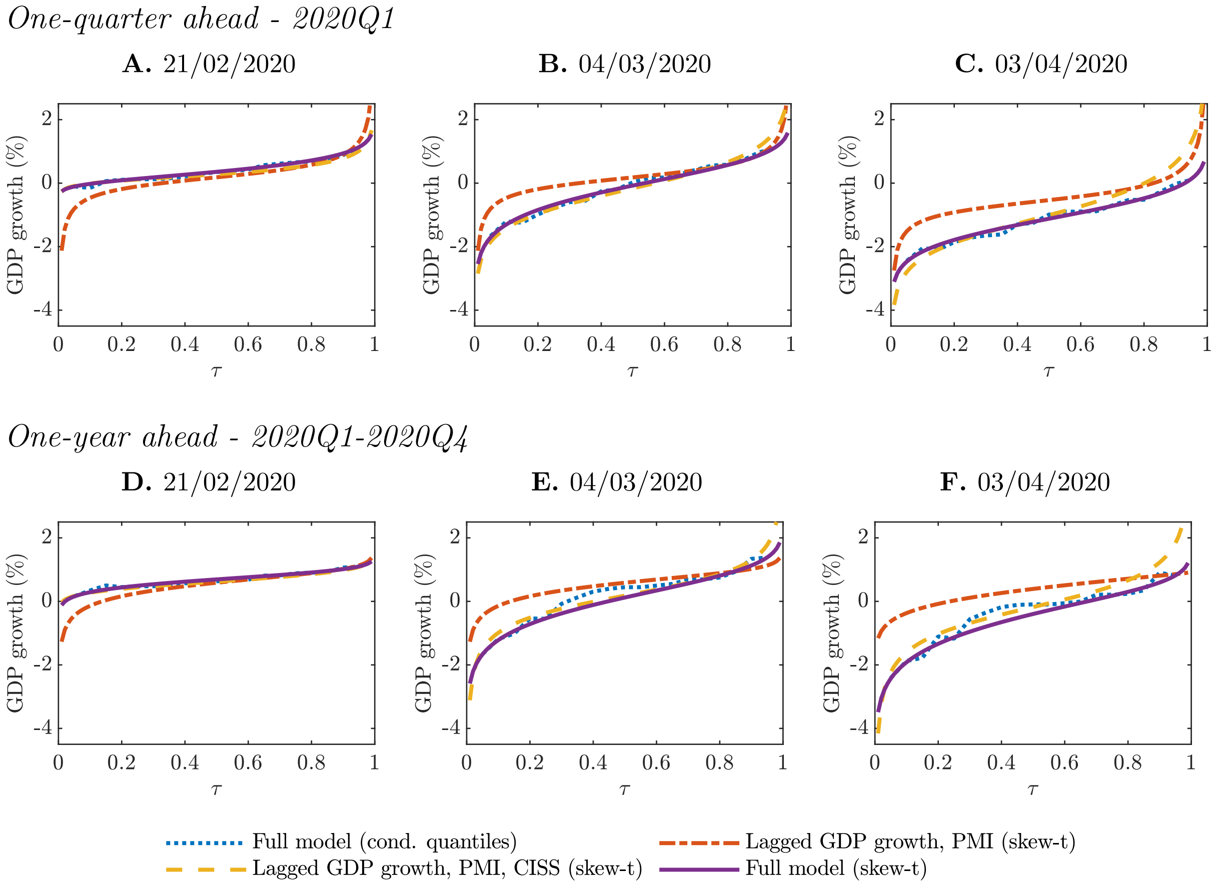
III.C.1 Skewed t-Distribution, Probability Density and Model Performance

Figure 5 plots the estimated conditional quantile distributions of the full model and three versions of the fitted inverse cumulative skewed t-distributions, one conditional on PMI and lagged GDP growth, one conditional on CISS, PMI and lagged GDP growth and one on the complete model, for three sample dates in 2020Q1. The first date on February 21, 2020 refers to the period before the pandemic disease shock hit the US economy and when the flash PMI for February was released. The second date on 4 March 2020 refers to the next day after the FED lowered its policy rate by 50 basis points, surprising the markets as well as the US President Trump. The third date on 3 April 2020 refers to the period when the shock clearly manifested in the US and the final PMI for March 2020 was released, broadly confirming the harsh economic reality deducted from the flash release on March 24, 2020 (see Panel A of Figure 2). Before the pandemic shock, the distribution conditional on the macro variable only is below the distribution conditional on both macro and financial variables, especially in the left tail. Two weeks later, the narrative is overturned. The distribution conditional on the macro variable only remains invariant, because the final PMI release for February confirmed the flash release. Conversely, both models including financial variables yield conditional distributions, which shift sharply downwards and skew to the left. This outcome is reinforced and corroborated at the beginning of April, which suggests that financial variables pointed to downside risks to economic activity much earlier than the macro factor. The negative implications of the pandemic disease shock is even stronger one-year ahead over the entire 2020.

Table 4 shows that the median and the mean of GDP growth predicted one-quarter ahead for 2020Q1 with the models including financial variables starts to decline steadily from February, 21 and turns negative on March 13, 2020, while the model with the macro factor only still suggests a stable outlook relative to February. The model with the macro factor only suggests a forthcoming economic contraction with the flash PMI release on March 24, 2020 and the foreseen economic contraction is only half compared to the very precise prediction by the model including financial variables.

In the case of the Covid-19 recession, which is driven purely by an unexpected random shock, it could be argued that the spike in risk premia and the fall in output happens contemporaneously, in line with the argument by Plagborg-Møller et al. (2020). Yet the timely information provided by the financial markets since the last week of February was

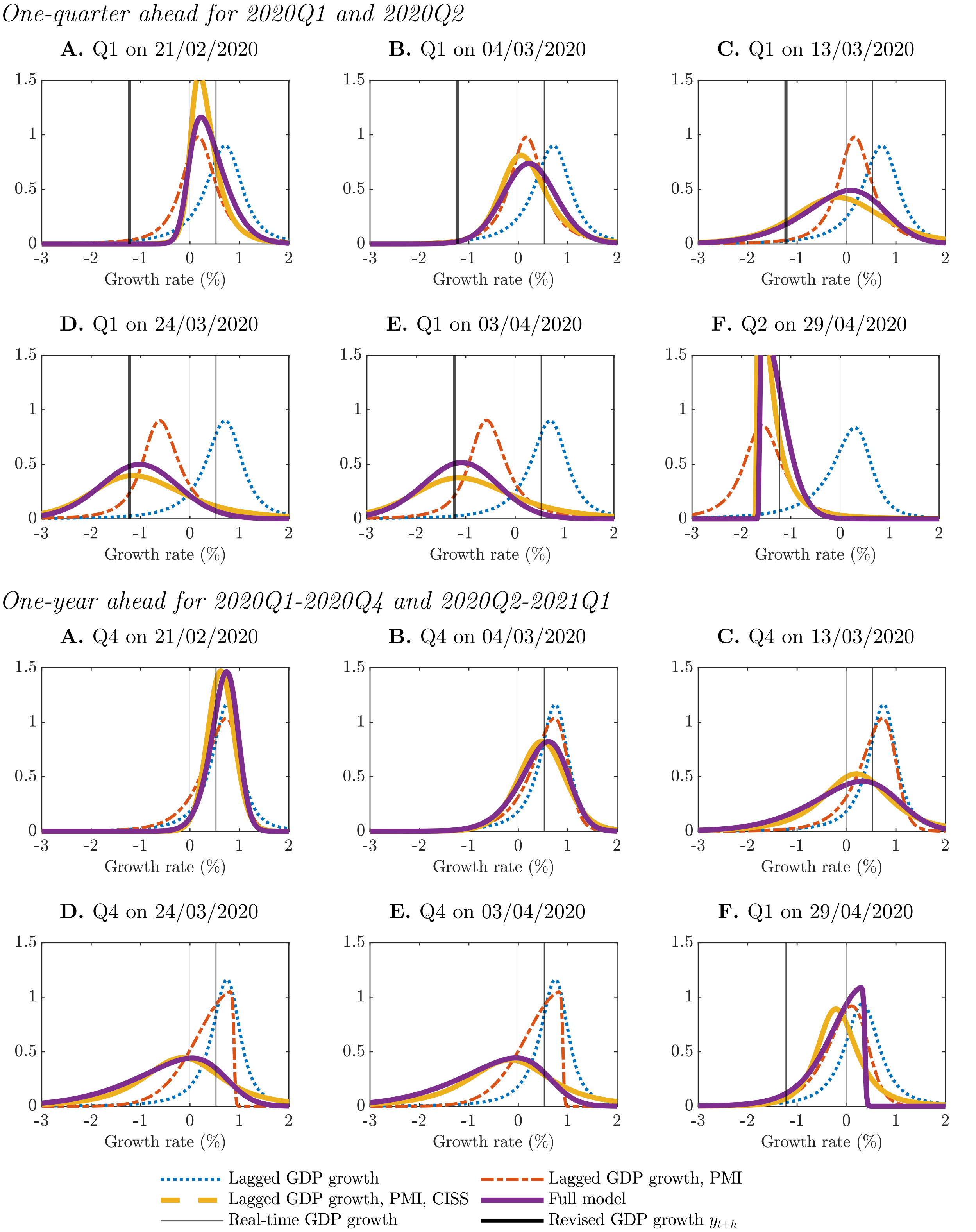
Figure 5: Covid-19 Recession - Quantiles and Skewed t-Distribution of GDP growth



Notes: The panels in this figure show the conditional quantiles and the skewed t-inverse cumulative distribution functions for one-quarter ahead and one-year ahead real GDP growth of the 'Full model' including lagged GDP growth, PMI, CISS and corporate spreads. For comparison, we also report the skew t-inverse cumulative distribution functions obtained by fitting the quantiles obtained by conditioning only on lagged GDP and PMI as well as on lagged GDP growth, PMI and CISS. Three vintages are shown on 21 February 2020, 4 March 2020 and 3 April 2020. GDP growth one-year ahead is defined as $y_{t+4} = \frac{1}{4}\sum_{h=1}^{4} y_{t+h}$ (i.e. year-on-year quarterly real GDP growth).

cardinal for the important fiscal and monetary policy decisions taken by the US policymakers in the first two weeks of March 2020. Moreover, the prediction of GDP growth in 2020Q1 with the model including financial variables is much more precise, as documented by the higher predicted score, the very low absolute prediction error in every March vintage and the lower MSFE computed using either the median, or the mean or the mode (see Tables 4 and 5). Figure 6 shows the four model-specific versions of the fitted conditional probability density functions of GDP growth for six vintages between February 21 and April 29, 2020. The comparison of the results indicates that the model with the macro factor only is characterized by a density function, which is to the left of that estimated with a model using only lagged GDP growth in all vintages, suggesting an expected slow in economic growth relative to past regularities. However, the model including also financial variables shows skewed left-tails from the first week of March, signaling a higher risk of sizeable negative GDP growth rates.

Figure 6: Covid-19 Recession - Probability Densities of GDP Growth



Notes: Each panel shows the skew-*t* probability densities for four different models and the predictive quantiles for the full model. 'Full model' refers to the model that includes lagged GDP growth, PMI, CISS and corporate spreads of non-financial corporations. The title of each panel indicates the real-time date of the forecast and the predicted quarter(s). GDP growth one-year ahead is defined as $y_{t+4} = \frac{1}{4}\sum_{h=1}^{4} y_{t+h}$ (i.e. year-on-year quarterly real GDP growth).

Table 4: Covid-19 Recession - Out-of-Sample Accuracy of the Density Forecasts of GDP Growth

	One-quarter ahead						*One-year ahead*					
	$21/2^a$	$04/3^a$	$13/3^a$	$24/3^a$	$03/4^a$	$23/4^b$	$21/2^c$	$04/3^c$	$13/3^c$	$24/3^c$	$03/4^c$	$23/4^d$
Revised GDP growth[1]	-1.23	-1.23	-1.23	-1.23	-1.23							
Median												
GDP_{t-1}	0.66	0.66	0.66	0.66	0.66	0.17	0.70	0.70	0.70	0.70	0.70	0.31
GDP_{t-1}, PMI	0.18	0.18	0.18	-0.57	-0.53	-1.55	0.59	0.59	0.59	0.38	0.39	-0.02
GDP_{t-1}, PMI, CISS	0.28	0.13	-0.16	-1.01	-1.01	-1.44	0.62	0.47	0.18	-0.15	-0.18	-0.17
Full model	0.36	0.23	-0.08	-1.04	-1.12	-1.33	0.69	0.51	0.12	-0.30	-0.40	-0.12
Mean												
GDP_{t-1}	0.56	0.56	0.56	0.56	0.56	-0.04	0.62	0.62	0.62	0.62	0.62	0.28
GDP_{t-1}, PMI	0.21	0.21	0.21	-0.49	-0.46	-1.50	0.49	0.49	0.49	0.28	0.29	-0.10
GDP_{t-1}, PMI, CISS	0.35	0.18	-0.14	-0.90	-0.91	-1.27	0.63	0.47	0.16	-0.16	-0.19	-0.12
Full model	0.42	0.24	-0.16	-1.04	-1.14	-1.27	0.67	0.46	0.02	-0.45	-0.55	-0.25
Absolute Prediction Error w.r.t. Median of the Predictive Distribution												
GDP_{t-1}	1.88	1.88	1.88	1.88	1.88							
GDP_{t-1}, PMI	1.41	1.41	1.41	0.66	0.69							
GDP_{t-1}, PMI, CISS	1.51	1.35	1.06	0.22	0.22							
Full model	1.58	1.45	1.15	0.19	0.11							
Absolute Prediction Error w.r.t. Mean of the Predictive Distribution												
GDP_{t-1}	1.79	1.79	1.79	1.79	1.79							
GDP_{t-1}, PMI	1.44	1.44	1.44	0.74	0.77							
GDP_{t-1}, PMI, CISS	1.58	1.41	1.08	0.33	0.32							
Full model	1.64	1.46	1.07	0.18	0.09							
Predictive Score												
GDP_{t-1}	0.03	0.03	0.03	0.03	0.03							
GDP_{t-1}, PMI	0.04	0.04	0.04	0.24	0.21							
GDP_{t-1}, PMI, CISS	0.00	0.03	0.21	0.40	0.37							
Full model	0.00	0.02	0.18	0.48	0.51							

Notes: This table shows the median, the mean, the absolute prediction error and the predictive score. The absolute prediction error is defined as the absolute value of the difference between the revised data on GDP growth and the central tendency (mean or median) of the real-time predictive distributions of GDP growth. The predictive score is the predictive distribution evaluated at the realized value of GDP growth. Lower absolute prediction errors and higher predictive scores indicate more accurate predictions. ([1]) GDP growth one quarter ahead is measured as quarterly log difference, y_{t+1}. GDP growth one-year ahead is defined as $y_{t+4} = \frac{1}{4}\sum_{h=1}^{4} y_{t+h}$ (i.e. year-on-year quarterly real GDP growth). ([a]) Prediction for q-o-q growth rate in 2020Q1. ([b]) Prediction for q-o-q growth rate in 2020Q2. ([c]) Prediction for q-o-q annual growth rate from 2020Q1 to 2020Q4. ([d]) Prediction for q-o-q annual growth rate from 2020Q2 to 2021Q1. GDP growth one-year ahead is defined as $y_{t+4} = \frac{1}{4}\sum_{h=1}^{4} y_{t+h}$ (i.e. year-on-year quarterly real GDP growth).

After the fiscal and monetary policy decisions have calmed financial markets in April, the resulting decline in the financial stress indicator and long-term risk premia, as measured by the CISS and corporate spreads, have squeezed the probability densities as estimated on April 29, 2020 (see Panel F of Figure 6). Only at the end of April, the unprecedented negative outturn for the macro factor in April 2020 (e.g. the flash Markit PMI plummeted to 27.4) has shifted the probability density estimated with the macro factor only close to prediction provided already on March 24 (five weeks earlier) by the model including financial markets.

Table 5: Covid-19 Recession - Mean Squared Forecast Errors

	One-quarter ahead		
	Median	Mean	Mode
GDP_{t-1}	3.54	3.20	3.75
GDP_{t-1}, PMI	1.37	1.47	1.32
GDP_{t-1}, PMI, CISS	1.06	1.17	0.94
Full model	1.20	1.20	1.19

Notes: This table shows the MSFE computed as the average of the squared difference between the revised data on GDP growth and (i) the median, (ii) the mean, and (iii) the mode of the real-time predictive distributions of GDP growth, using the six vintages of the Great Recession.

Table 6: Macroeconomic Risk during the Covid-19 Recession

	One-quarter ahead						*One-year ahead*					
	21/2[a]	04/3[a]	13/3[a]	24/3[a]	03/4[a]	23/4[b]	21/2[c]	04/3[c]	13/3[c]	24/3[c]	03/4[c]	23/4[d]
5% Shortfall												
GDP_{t-1}	-2.03	-2.03	-2.03	-2.03	-2.03	-3.37	-1.42	-1.42	-1.42	-1.42	-1.42	-1.91
GDP_{t-1}, PMI	-1.66	-1.66	-1.66	-2.35	-2.32	-3.57	-0.96	-0.97	-0.97	-0.96	-0.95	-1.54
GDP_{t-1}, PMI, CISS	-0.20	-0.98	-2.46	-3.26	-3.44	-1.68	0.05	-0.67	-2.54	-3.28	-3.46	-1.49
Full model	-0.20	-0.90	-2.22	-2.79	-2.86	-1.62	-0.01	-0.78	-2.23	-2.97	-3.08	-1.77
Upside Entropy												
GDP_{t-1}	-0.03	-0.03	-0.03	-0.03	-0.03	-0.04	-0.02	-0.02	-0.02	-0.02	-0.02	-0.09
GDP_{t-1}, PMI	-0.07	-0.07	-0.07	0.37	0.35	1.03	-0.07	-0.07	-0.07	0.07	0.07	0.20
GDP_{t-1}, PMI, CISS	0.01	-0.12	-0.18	0.18	0.16	1.20	0.00	-0.16	-0.14	-0.07	-0.06	0.14
Full model	-0.08	-0.13	-0.15	0.52	0.64	1.43	0.05	-0.14	-0.22	-0.06	0.02	0.60
Downside Entropy												
GDP_{t-1}	0.04	0.04	0.04	0.04	0.04	0.47	0.04	0.04	0.04	0.04	0.04	0.46
GDP_{t-1}, PMI	0.52	0.53	0.53	1.18	1.15	1.68	0.16	0.16	0.16	0.40	0.39	0.82
GDP_{t-1}, PMI, CISS	0.65	0.62	0.82	1.38	1.38	2.28	0.25	0.31	0.62	0.96	0.98	0.99
Full model	0.52	0.52	0.76	1.44	1.48	2.13	0.14	0.26	0.72	1.11	1.19	0.92
Probability of Contraction												
GDP_{t-1}	14	14	14	14	14	38	10	10	10	10	10	26
GDP_{t-1}, PMI	33	33	33	84	83	96	14	14	14	24	24	52
GDP_{t-1}, PMI, CISS	11	40	57	81	80	97	1	17	41	57	57	64
Full model	12	34	54	90	93	100	2	18	45	63	67	61
Expected Value in case of Contraction												
GDP_{t-1}	-0.90	-0.90	-0.90	-0.90	-0.90	-0.85	-0.82	-0.82	-0.82	-0.82	-0.82	-0.60
GDP_{t-1}, PMI	-0.47	-0.47	-0.47	-0.75	-0.73	-1.62	-0.47	-0.47	-0.47	-0.40	-0.40	-0.48
GDP_{t-1}, PMI, CISS	-0.11	-0.35	-0.86	-1.33	-1.38	-1.36	-0.11	-0.31	-0.76	-0.94	-0.99	-0.47
Full model	-0.11	-0.36	-0.78	-1.20	-1.25	-1.28	-0.15	-0.36	-0.80	-1.01	-1.04	-0.54

Notes: This table summarises the macroeconomic risk in economic activity using five indicators. The 5% expected shortfall measures the expected value in the lower 5% tail of the conditional probability density. The downside entropy measures the conditional risks to the downside in excess of the downside risks predicted by the unconditional distribution, evaluated over the entire 50% left tail of the conditional distribution. The upside entropy measures the conditional risks to the upside in excess of the upside risks predicted by the unconditional distribution, evaluated over the entire 50% right tail of the conditional distribution. The probability of a contraction is the CDF evaluated at zero growth rate. The expected value in case of a contraction is the expected value conditional on a contraction. [a] Prediction for q-o-q growth rate in 2020Q1. [b] Prediction for q-o-q growth rate in 2020Q2. [c] Prediction for q-o-q annual growth rate from 2020Q1 to 2020Q4. [d] Prediction for q-o-q annual growth rate from 2020Q2 to 2021Q1. GDP growth one-year ahead is defined as $y_{t+4} = \frac{1}{4}\sum_{h=1}^{4} y_{t+h}$ (i.e. year-on-year quarterly real GDP growth).

III.C.2 Macro Risk Evaluation during the Covid-19 Recession

Policymakers are strongly concerned with the downside risks to the GDP growth forecast due to the uncertainty surrounding the pandemic outbreak. We quantify the risk to GDP growth in real time and provide the results in Table 6.

The models with financial variables are characterized by a lower 5% expected shortfall, a higher downside entropy and a higher probability of contraction since the first week of March. By mid-March the probability of contraction is predicted at 50-60%, which surges to 90% a few days later. The expected value in case of a contraction is evaluated between -1.20% and -1.28%, which is slightly below the expected value (between -1.04% and -1.27%) and precisely predicts the actual real GDP growth flash estimate for the US economy in 2020Q1 (i.e. -1.23%). In summary, financial variables do help forecast economic activity and evaluate macroeconomic risk also during the Covid-19 Recession.

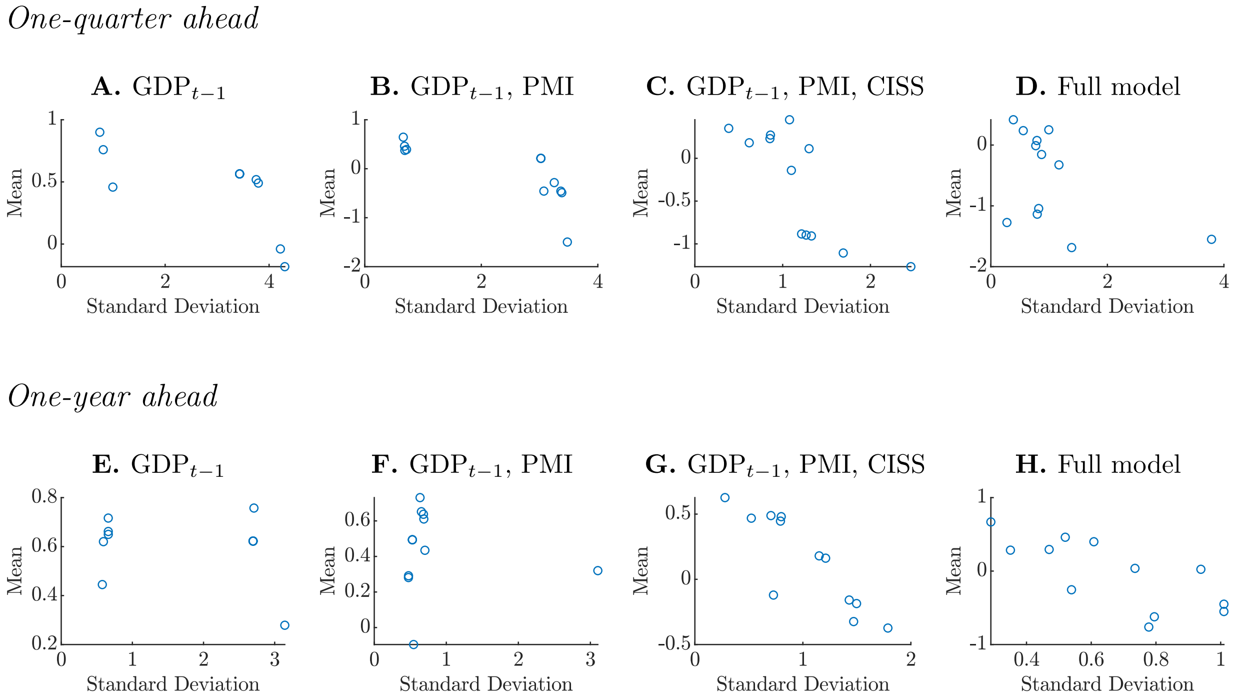
Finally, Figure 7 shows the relation between mean and the standard deviation of the one-quarter ahead and one-year ahead predictive distributions for GDP growth across the twelve vintages covering the Great Recession and the Covid-19 Recession obtained with the four different models: i.e., using only lagged GDP growth (A and E), using lagged GDP growth and PMI (B and F), using lagged GDP growth, PMI and CISS (C and G) and using the full model with lagged GDP growth, PMI, CISS and corporate spreads (D and H). Our results confirm Adrian et al. (2019)'s findings that GDP growth is vulnerable. The conditional mean and the conditional volatility of GDP growth move in opposite directions in both models with financial variables, implying that downside risks move more strongly than upside risks.

III.C.3 Covid-19: Lessons from the Spanish Flu

The literature on the macroeconomic impact of the Covid-19 pandemic disease is fast-growing (e.g., Alvarez et al., 2020; Atkeson, 2020; Baqaee and Farhi, 2020; Bodenstein et al., 2020; Brodeur et al., 2020; Jones et al., 2020; Coibion et al., 2020; Correia et al., 2020; Eichenbaum et al., 2020a,b; Faria-e-Castro, 2020; Favero et al., 2020; Fornaro and Wolf, 2020; Glover et al., 2020; Gonzalez-Eiras and Niepelt, 2020; Guerrieri et al., 2020; Jordà et al., 2020; Kaplan et al., 2020; Krueger et al., 2020; Primiceri and Tambalotti, 2020; Stock, 2020). A large variety of methods are used to assess the economic implications from the pandemic outbreak, because the shock is non-normal and a rare event.[16] We aim at gaining insights from the the 1918-1920 Great Influenza Pandemic (known also as Spanish flu). Given the advances in public-health care, the stringent lockdown measures and the general knowledge about the disease, as pointed out by Barro et al. (2020), it is unlikely that Covid-19 pandemic will reach the death rates across countries caused by the Spanish flu (e.g. 2% of the world's population). However, the two diseases share similar features in terms of infection rates, having affected

[16]Disaster risks are associated to non-normal shocks, whose implications for asset prices, consumption and welfare have been investigated by the literature (see, e.g., Barro, 2006, 2009; Barro and Jin, 2011; Berkman et al., 2011; Barro and Ursúa, 2012; Gabaix, 2012; Nakamura et al., 2013; Farhi and Gabaix, 2016).

Figure 7: Conditional Mean and Volatility of Predictive Densities



Notes: The panels in this figure show the mean and the standard deviation of one-quarter ahead and one-year ahead GDP growth across the six Great Recession vintages plus the six Covid-19 Recession vintages obtained with four different models: lagged GDP growth (A and E); lagged GDP growth and PMI (B and F); lagged GDP growth, PMI and CISS (C and G); lagged GDP growth, PMI, CISS and corporate spreads (D and H). GDP growth one-year ahead is defined as $y_{t+4} = \frac{1}{4}\sum_{h=1}^{4} y_{t+h}$ (i.e. year-on-year quarterly real GDP growth).

almost all countries in the world, and in terms of restrictions on economic activity and travelling imposed or self-imposed (i.e. social distancing policies), well documented in the case of United States. (e.g. Bootsma and Ferguson, 2007; Markel et al., 2007; Wheelock, 2020).[17]

We revisit the analysis carried out by Barro et al. (2020) using the same cross-sectional database with 42 countries over the sample period 1901-1929 through the lenses of the non-linear model applying the two-step semi-parametric approach discussed in Section III, but in a panel setting. The non-linear model allows to trace the impact of a pandemic on different quantiles of the GDP growth distribution and, in addition, by fitting a skewed-t distribution, it facilitates the computation of the associated macro risk, which requires the integration of a predictive density.

The key regressors are the death rates due to the Spanish flu and the death rates due to the Great War, because it is important to control for the effects of the World War I. The

[17] An example of social distancing policy put in place in Europe in 1918 is detailed in these articles about Liverpool (https://www.liverpoolecho.co.uk/news/liverpool-news/social-distancing-liverpool-during-spanish-18139281) and Milan (https://www.fondazionecorriere.corriere.it/ai-tempi-dellinfluenza-spagnola/).

Table 7: Partial Effect of the Spanish Flu on Macroeconomic Risk in 1918-1920

	Median			Mean			Exp. Value / Contract.			5% Shortfall		
	1918	1919	1920	1918	1919	1920	1918	1919	1920	1918	1919	1920
World	-3.39	-0.67	-0.22	-4.41	-1.71	-0.56	-8.21	-2.41	-0.79	-32.25	-11.18	-3.67
Argentina	-0.22	-0.24	0.00	-0.56	-0.60	0.00	-0.79	-0.85	0.00	-3.65	-3.93	0.00
Australia	-4.48	-0.34	-0.05	0.00	-0.86	-0.13	-3.89	-1.21	-0.18	-13.62	-5.59	-0.82
Austria	-9.47	-0.28	0.00	-2.48	-0.73	0.00	-11.74	-1.03	0.00	-44.55	-4.74	0.00
Belgium	-0.97	-0.15	-0.02	-2.47	-0.39	-0.04	-3.44	-0.55	-0.06	-15.99	-2.56	-0.25
Brazil	-0.66	-0.28	0.00	-1.68	-0.72	0.00	-2.36	-1.02	0.00	-10.95	-4.72	0.00
Canada	-3.19	-0.21	-0.10	-1.28	-0.53	-0.24	-4.08	-0.75	-0.33	-16.46	-3.49	-1.51
Chile	-0.09	-0.73	-0.05	-0.22	-1.87	-0.12	-0.30	-2.62	-0.17	-1.34	-12.16	-0.76
China	-0.82	-0.89	-0.30	-1.97	-2.28	-0.76	-2.79	-3.18	-1.07	-13.01	-14.77	-4.94
Colombia	-0.60	0.00	-0.03	-1.53	0.00	-0.08	-2.15	0.00	-0.11	-9.98	0.00	-0.50
Denmark	-0.23	-0.11	-0.08	-0.59	-0.28	-0.21	-0.83	-0.39	-0.28	-3.83	-1.76	-1.27
Egypt	-1.08	-0.25	-0.14	-2.76	-0.64	-0.35	-3.84	-0.91	-0.49	-17.82	-4.20	-2.25
Finland	n.a.	-0.20	-0.03	n.a.	-0.52	-0.09	n.a.	-0.73	-0.12	n.a.	-3.39	-0.53
France	-4.38	-0.31	0.00	-1.73	-0.78	0.00	-5.57	-1.10	0.00	-22.65	-5.08	0.00
Germany	-9.86	-0.03	-0.14	-2.06	-0.06	-0.36	-11.96	-0.09	-0.51	-42.55	-0.40	-2.34
Greece	-2.46	-0.03	0.00	-1.38	-0.07	0.00	-3.57	-0.10	0.00	-14.09	-0.43	0.00
Iceland	-0.60	-0.28	-0.21	-1.53	-0.72	-0.54	-2.14	-1.02	-0.76	-9.93	-4.72	-3.53
India	-5.54	-1.17	-0.36	-14.26	-2.99	-0.92	-19.20	-4.16	-1.29	-88.01	-19.31	-5.97
Indonesia	-3.08	-1.04	0.00	-7.94	-2.66	0.00	-10.88	-3.70	0.00	-50.63	-17.16	0.00
Italy	-3.52	-0.08	0.00	-3.73	-0.21	0.00	-7.45	-0.29	0.00	-29.50	-1.31	0.00
Japan	-0.68	-0.25	-0.51	-1.41	-0.64	-1.30	-2.05	-0.90	-1.83	-9.73	-4.17	-8.50
Malaysia	-1.67	-0.09	0.00	-4.28	-0.23	0.00	-5.97	-0.31	0.00	-28.00	-1.39	0.00
Mexico	-2.10	0.00	-0.71	-5.39	0.00	-1.80	-7.47	0.00	-2.53	-34.95	0.00	-11.75
Netherlands	-0.75	-0.19	-0.03	-1.91	-0.48	-0.08	-2.68	-0.67	-0.11	-12.46	-3.11	-0.49
New Zealand	-5.85	-0.04	-0.12	-1.81	-0.09	-0.31	-7.44	-0.12	-0.43	-26.92	-0.56	-1.96
Norway	-0.61	-0.15	-0.01	-1.56	-0.39	-0.04	-2.19	-0.54	-0.05	-10.14	-2.50	-0.22
Peru	-0.13	-0.13	-0.27	-0.34	-0.34	-0.68	-0.47	-0.47	-0.96	-2.18	-2.18	-4.43
Philippines	-1.45	-1.11	0.00	-3.72	-2.85	0.00	-5.15	-3.96	0.00	-23.91	-18.40	0.00
Portugal	-2.66	-0.12	0.00	-5.51	-0.32	0.00	-9.00	-0.44	0.00	-34.41	-2.03	0.00
Russia	-4.78	-0.54	-0.08	-4.59	-1.37	-0.21	-9.51	-1.92	-0.29	-38.12	-8.92	-1.29
Singapore	-1.35	-0.20	-0.22	-3.46	-0.50	-0.55	-4.79	-0.71	-0.78	-22.23	-3.27	-3.63
South Africa	-3.19	-1.69	0.00	-7.36	-4.34	0.00	-10.30	-6.05	0.00	-48.37	-28.44	0.00
South Korea	-1.06	-0.33	-0.50	-2.70	-0.84	-1.28	-3.75	-1.19	-1.81	-17.42	-5.50	-8.40
Spain	-1.43	-0.19	-0.24	-3.66	-0.48	-0.61	-5.07	-0.69	-0.86	-23.51	-3.17	-3.99
Sri Lanka	-0.78	-1.36	-0.23	-2.00	-3.48	-0.59	-2.80	-4.82	-0.84	-12.99	-22.36	-3.88
Sweden	-0.64	-0.19	-0.03	-1.63	-0.48	-0.08	-2.29	-0.68	-0.11	-10.62	-3.13	-0.51
Switzerland	-0.73	-0.15	-0.17	-1.86	-0.37	-0.43	-2.61	-0.52	-0.61	-12.11	-2.40	-2.80
Taiwan	-0.78	-0.02	-0.71	-1.85	-0.06	-1.81	-2.63	-0.08	-2.54	-12.28	-0.38	-11.81
Turkey	-7.22	-0.07	0.00	-3.25	-0.18	0.00	-10.63	-0.24	0.00	-39.81	-1.06	0.00
United Kingdom	-5.89	-0.17	0.00	-1.09	-0.42	0.00	-6.57	-0.60	0.00	-23.77	-2.75	0.00
United States	-1.32	-0.10	-0.07	-1.27	-0.26	-0.19	-2.46	-0.36	-0.26	-8.94	-1.62	-1.15
Uruguay	-0.17	-0.07	-0.05	-0.44	-0.18	-0.13	-0.63	-0.26	-0.18	-2.90	-1.17	-0.83
Venezuela	-1.35	-0.36	0.00	-3.45	-0.92	0.00	-4.78	-1.30	0.00	-22.17	-5.99	0.00

Notes: This table shows the partial effect of the Spanish flu on the expected value of countries' real per-capita GDP growth, the expected value in case of contraction, which measures the expected value conditional on a contraction, and the 5% shortfall, which measures the expected value in the lower 5% tail of the conditional probability density. The partial effect is computed as $\mathcal{S}\left(\hat{f}_{yt}\right) - \mathcal{S}\left(\hat{f}_{yt|\ deaths_t^{flu}=0}\right)$, where $\mathcal{S}$ is one of the three described metrics and $\hat{f}_{yt}$ is the estimated conditional distribution.

partial effects of the Spanish flu are evaluated as follows $\mathcal{S}\left(\hat{f}_{yt}\right) - \mathcal{S}\left(\hat{f}_{yt|\ deaths_t^{flu}=0}\right)$, where $\mathcal{S}$ is the metric of interest, $\hat{f}_{yt}$ is the estimated conditional distribution and $\hat{f}_{yt|\ deaths_t^{flu}=0}$ is $\hat{f}_{yt}$ evaluated setting to zero the death rates due to the Spanish flu. The metrics reported in Table 7 are the median, the mean, the expected value of countries' real per capita GDP growth in case of contraction and the 5% shortfall.

Exploiting the exogenous variation in death rates due to the Spanish flu across 42 countries between 1918 and 1920, while controlling for the death rates caused by the Great War, Barro et al. (2020) finds that the typical country's real per capita GDP growth dropped by 6% over the cumulated period 1918-1920 as a consequence of the Spanish flu. We confirm the 6.7% drop on average (see Table 7), with most of the impact occurring immediately in 1918 (-4.4%). As for the downside risk over the cumulated period 1918-1920, we estimate for the typical country the expected value in case of a contraction due to the pandemic disease to be –11.4% (-8.2% in 1918) and the 5% expected shortfall to amount to -47.1% (-32.2% in 1918); according to all three statistics, about 70% of the economic damage occurring in the first year. Even though this attempt can only provide a best guess in the Covid-19 context, the findings from the Spanish flu suggest that the risk of a sharp fall in economic activity for the typical country close to two digits cannot be dismissed entirely.

In the specific case of the US economy, Correia et al. (2020) estimate that the pandemic caused an 18% fall in US manufacturing output and a 23% decline in US manufacturing employment. Using the specific death rates for the US, our estimates suggest an average decline in the US real per-capita GDP growth by 1.3% in 1918 and 0.3% in 1919 as also found by Barro et al. (2020), in line with Burns and Mitchell (1946)'s views that the US recession in 1918-1919 was brief and of moderate amplitude, a view corroborated by Velde (2020).

IV The Role of other Macro and Financial Variables

The main analysis has been carried out using the Markit PMI, because it is an indicator closely monitored by policymakers, academics and investors. It is more timely. In this section, we show that the key result of the paper that financial factors do play a role in forecasting both the first and higher moments of GDP growth distribution once controlling for macro factors remains valid to the use of alternative macroeconomic variables. Specifically, we use indicators whose predictive power for real GDP growth has been emphasised in the literature and the media, such as the Manufacturing ISM, the CFNAI and CBLI. The data are collected using real-time vintages. Finally, we also investigate how sensitive the conditional quantile function is to the slope of the yield curve.

IV.A ISM, CFNAI and CBLI

The ISM also compiles manufacturing surveys on a monthly basis by polling businesses, covering all sectors of the US economy. As already discussed and shown in Figure 2, it comoves tightly with Markit PMI and with real GDP growth.

The CFNAI is a weighted average of 85 existing monthly indicators of national economic activity, which are drawn from four broad categories of data measuring some aspect of overall macroeconomic activity: production and income; employment, unemployment, and hours; personal consumption and housing; and sales, orders, and inventories. It corresponds to the index of economic activity developed by Stock and Watson (1999), which provides a useful gauge on current and future economic activity and inflation in the US.

The CBLI is a composite of macroeconomic and financial variables calculated by The Conference Board, a non-governmental organization. It is constructed to summarize and reveal common turning point patterns in economic data, signalling peaks and troughs in the business cycle. The CBLI incorporates the data from 10 economic releases that traditionally have peaked or bottomed ahead of the business cycle, drawn from production, unemployment, hours, orders, building permits, consumer expectations, money supply (M2) and financial variables, such as the Standard & Poor's 500 Stock Index and the interest rate spread, defined as 10-year Treasury versus Federal Funds target.

Tables 8 and 9 summarise the key results for the Great Recession. We show the results of two models, the model with one of the above mentioned macro variables together with lagged real GDP growth and the full model including the CISS and the corporate spreads. The benchmark full model shows, as a reference, the already discussed results of the model with the Markit PMI. The results are clear in terms of model performance. The full model including the CISS and the corporate spreads is characterized by lower MSFEs and higher predictive scores in the case of ISM and CBLI, but not in the case of the CFNAI.[18] However, compared to our benchmark model, which uses the Markit PMI, the CFNAI does not perform better. The results also suggest that the CBLI is a good alternative to our benchmark model yielding a similar performance. But it is a composite indicator including both macro and financial variables and, hence, it cannot answer the main question of the paper. The results about the macroeconomic risk and quarterly prediction errors are reported in the Appendix.

The comparison of the performance in the case of the Covid-19 recession is not provided, because these indicators were released much later. The Manufacturing ISM was published on 1 April showing a mild decline by 2%, the CBLI was published on 17 April showing a decline by 6.7% and the CFNAI was published on 20 April showing a substantial decline.

In summary, also other macro factors cannot beat the additional forecast insights for the first and higher moments of the conditional distribution of GDP growth provided by financial variables, such the CISS and corporate spreads.

[18] The prediction errors and the evaluation of the macroeconomic risk using other macroeconomic variables are provided in the Appendix.

Table 8: Great Recession - Accuracy of the Density Forecasts with other Macro Variables

	One-quarter ahead						*One-year ahead*					
	07Q4	08Q1	08Q2	08Q3	08Q4	09Q1	08Q3	08Q4	09Q1	09Q2	09Q3	09Q4
Revised GDP growth[1]	0.61	-0.57	0.52	-0.54	-2.16	-1.12	0.00	-0.69	-0.83	-0.99	-0.77	0.05
Median												
GDP_{t-1}, ISM	0.69	0.53	0.53	0.65	-0.16	-0.34	0.78	0.70	0.70	0.76	0.45	0.39
Full model with ISM	0.48	0.11	0.26	0.43	-1.09	-1.14	0.39	-0.04	0.30	0.32	-0.92	-0.80
GDP_{t-1}, CBLI	0.90	0.54	0.56	0.73	0.43	-0.02	0.82	0.64	0.66	0.74	0.59	0.36
Full model with CBLI	0.22	-0.36	0.05	0.24	-1.28	-1.53	0.29	-0.01	0.27	0.23	-0.80	-0.80
GDP_{t-1}, CFNAI	0.56	0.05	0.12	0.28	0.04	-1.29	0.71	0.46	0.49	0.58	0.44	-0.28
Full model with CFNAI	0.70	0.21	0.21	0.49	1.30	-1.09	0.64	0.39	0.46	0.55	0.22	-0.58
Benchmark full model	0.42	-0.08	0.24	0.16	-1.34	-1.27	0.38	-0.09	0.28	0.29	-0.96	-0.82
Mean												
GDP_{t-1}, ISM	0.69	0.49	0.50	0.64	-0.24	-0.43	0.72	0.63	0.64	0.70	0.42	0.35
Full model with ISM	0.33	-0.15	0.13	0.24	-1.48	-1.44	0.41	0.07	0.30	0.31	-0.75	-0.61
GDP_{t-1}, CBLI	0.91	0.56	0.58	0.73	0.47	-0.06	0.75	0.61	0.63	0.69	0.56	0.36
Full model with CBLI	0.26	-0.36	0.03	0.15	-1.57	-1.70	0.34	0.03	0.30	0.30	-0.60	-0.65
GDP_{t-1}, CFNAI	0.53	0.03	0.09	0.26	0.02	-1.31	0.66	0.42	0.44	0.53	0.39	-0.27
Full model with CFNAI	0.63	0.24	0.22	0.49	1.06	-0.98	0.54	0.22	0.31	0.41	0.22	-0.66
Benchmark full model	0.25	-0.33	0.07	-0.01	-1.69	-1.55	0.40	0.04	0.29	0.28	-0.76	-0.62
Predictive Score												
GDP_{t-1}, ISM	0.78	0.09	0.83	0.08	0.02	0.17	0.20	0.04	0.03	0.02	0.06	0.54
Full model with ISM	0.42	0.24	0.64	0.15	0.15	0.94	0.55	0.43	0.05	0.01	0.53	0.21
GDP_{t-1}, CBLI	0.73	0.02	1.77	0.02	0.00	0.05	0.04	0.00	0.00	0.00	0.00	0.01
Full model with CBLI	0.37	0.37	0.48	0.27	0.20	0.93	0.00	0.00	0.00	0.00	1.29	0.15
GDP_{t-1}, CFNAI	1.05	0.31	0.54	0.15	0.01	0.62	0.26	0.09	0.05	0.02	0.08	0.56
Full model with CFNAI	0.74	0.23	0.61	0.09	0.01	0.74	0.23	0.11	0.07	0.03	0.08	0.39
Benchmark full model	0.44	0.27	0.70	0.28	0.21	1.27	0.57	0.50	0.04	0.00	0.56	0.18

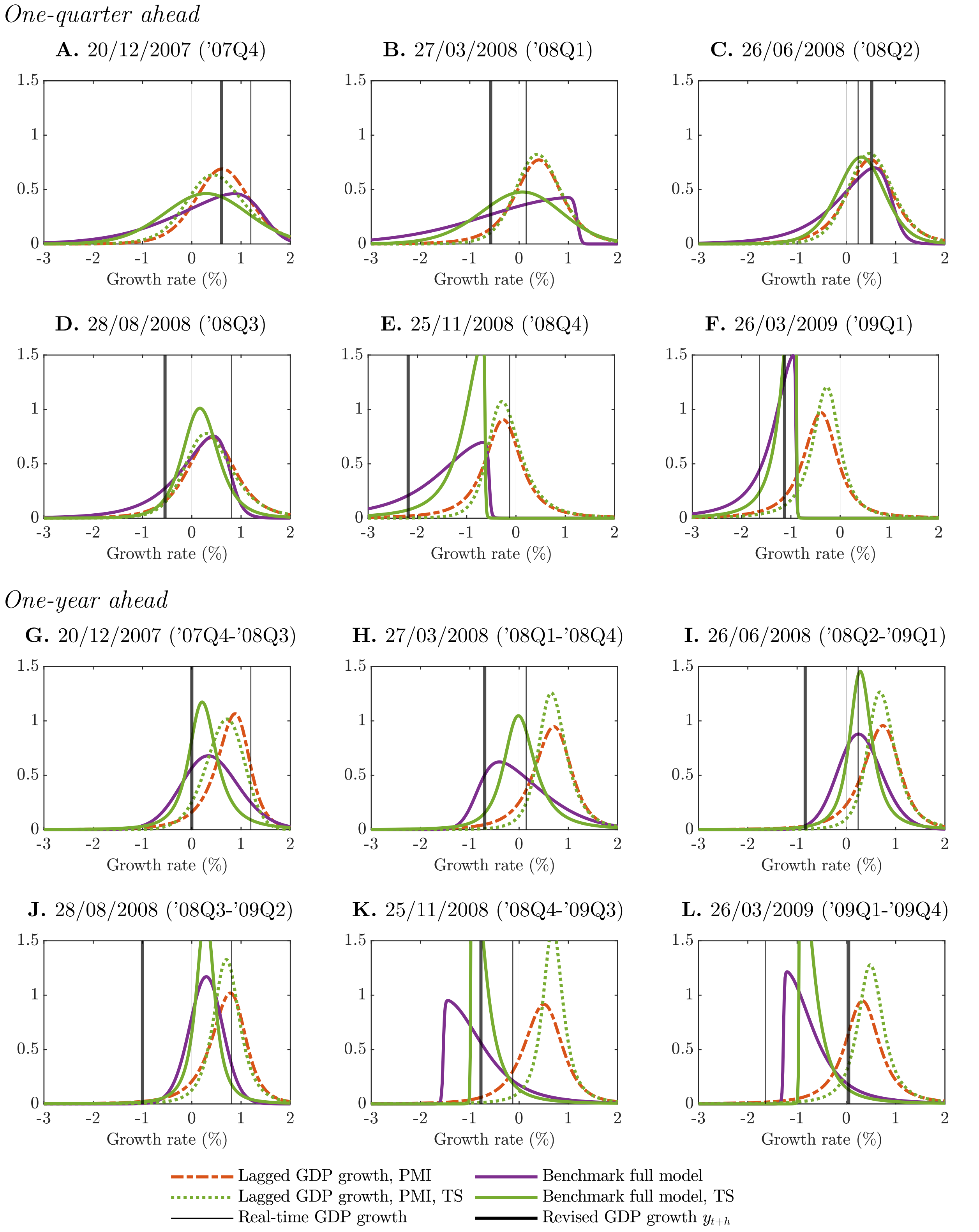
Notes: This table shows the absolute prediction error with respect to the mean of the predictive distribution and the predictive score. The former is defined as the absolute value of the difference between the revised data on GDP growth and the mean of the real-time predictive distributions of GDP growth. The latter is the predictive distribution evaluated at the realized value of the time series. Lower absolute prediction errors and higher predictive scores indicate more accurate predictions. ([1]) GDP growth one quarter ahead is measured as quarterly log difference, y_{t+1}. GDP growth one-year ahead is defined as $y_{t+4} = \frac{1}{4}\sum_{h=1}^{4} y_{t+h}$ (i.e. year-on-year quarterly real GDP growth).

IV.B Slope of the Yield Curve

Given the role of the slope of the yield curve in forecasting recessions (Estrella and Hardouvelis, 1991; Estrella and Mishkin, 1998), we also investigate whether the forecasting performance of the model improves when adding another financial variable, the spread between the 10-year and the 3-month Treasury yields. We adopt the same strategy. First, we run the forecast model including macro variables only with the best model including Markit PMI and lagged real GDP growth. Second, we assess the forecasting performance of a model by adding the term spread and finally, we consider the full model including the CISS and the corporate spreads.

The summary results are provided in Tables 10 and 11 and Figures 8 and 9. The forecast during the Great Recession suggests that the term spread does not provide any useful ad-

Figure 8: Term Spread - Probability Densities of GDP Growth during the Great Recession



Notes: Each panel shows the skewed-*t* probability densities for four different models and the predictive quantiles for the full model. 'Full model' refers to the model that includes lagged GDP growth, PMI, CISS and corporate spreads of non-financial corporations. The title of each panel indicates the real-time date of the forecast and the predicted quarter(s). The predictions for GDP growth one-year ahead predict the quarterly year-on-year growth rate.

Table 9: Great Recession - Mean Squared Forecast Errors with other Macro Variables

	One-quarter ahead			*One-year ahead*		
	Median	Mean	Mode	Median	Mean	Mode
GDP_{t-1}, ISM	1.23	1.14	1.29	1.61	1.48	1.72
Full model with ISM	0.45	0.27	0.85	0.73	0.70	0.93
GDP_{t-1}, CBLI	1.84	1.87	1.82	1.61	1.53	1.84
Full model with CBLI	0.33	0.27	0.99	0.67	0.69	0.59
GDP_{t-1}, CFNAI	1.04	1.01	1.06	1.28	1.19	1.47
Full model with CFNAI	2.33	2.06	2.55	1.18	0.99	1.35
Benchmark full model	0.26	0.18	0.97	0.70	0.68	0.84

Notes: This table shows the MSFE computed as the average of the squared difference between the revised data on GDP growth and (i) the median, (ii) the mean, and (iii) the mode of the real-time predictive distributions of GDP growth, using the six vintages of the Greast Recession.

ditional information in addition to the insights provided by the model with macroeconomic variables only. The probability densities of the models obtained with and without the term spread are very similar (see Figure 8). Panel A of Table 10 shows that the model with macro factors only and the model including the term spread yield similar means, predictive scores and MSFEs. Similarly, the complete model with all three financial variables does not perform better than our benchmark full model without the term spread. In the case of the Covid-19 recession, where we can evaluate the models' performance in 2020Q1, the model with term spread produces marginally lower absolute prediction errors and MSFEs and slightly higher prediction scores.[19] However, when looking at the probability densities shown in Figure 9 the model with term spread does not provide economically significant differences. The results about the macroeconomic risk and quarterly prediction errors are reported in the Appendix.

V Conclusions

Prior to the global financial crisis, financial variables did not play an important role in the analysis of the business cycle. After the Great Recession, the economic profession has been including financial mechanisms in the macro models and treating financial variables as key drivers of economic activity. They are either the source of financial shocks or amplifiers of the transmission mechanism of any other shock. Nevertheless, models with financial mechanisms do not provide insight to the forecast ability of financial variables, because random shocks are contemporaneous to macroeconomic developments. The literature is debating whether, once controlling for macro factors, financial variables provide additional insights to the forecast of real GDP growth and its conditional distribution. Given the timely publication of soft macro

[19]The prediction errors and the evaluation of the macroeconomic risk using the term spread are provided in the Appendix.

Table 10: Great Recession & Covid-19 - Accuracy of the Density Forecasts with Term Spread

	One-quarter ahead						*One-year ahead*					
Panel A: Great Recession	07Q4	08Q1	08Q2	08Q3	08Q4	09Q1	07Q4	08Q1	08Q2	08Q3	08Q4	09Q1
Revised GDP growth[1]	0.61	-0.57	0.52	-0.54	-2.16	-1.12	0.00	-0.69	-0.83	-0.99	-0.77	0.05
Median												
GDP_{t-1}, PMI	0.63	0.39	0.47	0.39	-0.27	-0.41	0.81	0.66	0.69	0.72	0.47	0.32
GDP_{t-1}, PMI, TS	0.51	0.40	0.50	0.36	-0.20	-0.30	0.67	0.69	0.73	0.71	0.69	0.50
GDP_{t-1}, PMI, TS, CISS	0.48	0.38	0.38	0.30	-0.74	-0.78	0.53	0.46	0.60	0.63	0.11	0.01
Full model with TS	0.29	0.03	0.29	0.18	-0.97	-1.10	0.24	0.03	0.30	0.27	-0.75	-0.72
Benchmark full model	0.42	-0.08	0.24	0.16	-1.34	-1.27	0.38	-0.09	0.28	0.29	-0.96	-0.82
Mean												
GDP_{t-1}, PMI	0.64	0.37	0.46	0.39	-0.28	-0.46	0.73	0.61	0.64	0.65	0.43	0.32
GDP_{t-1}, PMI, TS	0.56	0.42	0.52	0.41	-0.12	-0.34	0.65	0.73	0.77	0.72	0.70	0.52
GDP_{t-1}, PMI, TS, CISS	0.52	0.34	0.43	0.39	-0.55	-0.69	0.49	0.44	0.62	0.60	0.08	0.03
Full model and TS	0.29	0.00	0.28	0.19	-1.23	-1.26	0.29	0.11	0.34	0.27	-0.58	-0.55
Benchmark full model	0.25	-0.33	0.07	-0.01	-1.69	-1.55	0.40	0.04	0.29	0.28	-0.76	-0.62
Predictive Score												
GDP_{t-1}, PMI	0.69	0.14	0.78	0.16	0.02	0.20	0.16	0.05	0.03	0.02	0.06	0.66
GDP_{t-1}, PMI, TS	0.61	0.11	0.83	0.15	0.00	0.12	0.25	0.01	0.01	0.01	0.01	0.36
GDP_{t-1}, PMI, TS, CISS	0.41	0.24	0.53	0.25	0.11	0.46	0.35	0.08	0.03	0.02	0.18	0.70
Full model with TS	0.43	0.35	0.72	0.18	0.08	1.57	0.83	0.15	0.03	0.02	1.75	0.13
Benchmark full model	0.44	0.27	0.70	0.28	0.21	1.27	0.57	0.50	0.04	0.00	0.56	0.18

Panel B: Covid-19 Recession	21/2[a]	04/3[a]	13/3[a]	24/3[a]	03/4[a]	23/4[b]
Revised GDP growth[1]	-1.23	-1.23	-1.23	-1.23	-1.23	
Median						
GDP_{t-1}, PMI	0.18	0.18	0.18	-0.57	-0.53	-1.55
GDP_{t-1}, PMI, TS	0.06	0.08	0.11	-0.64	-0.63	-1.61
GDP_{t-1}, PMI, TS, CISS	0.16	-0.02	-0.43	-1.28	-1.33	-1.74
Full model with TS	0.24	0.11	-0.24	-1.17	-1.28	-1.50
Benchmark full model	0.36	0.23	-0.08	-1.04	-1.12	-1.33
Mean						
GDP_{t-1}, PMI	0.21	0.21	0.21	-0.49	-0.46	-1.50
GDP_{t-1}, PMI, TS	0.05	0.08	0.12	-0.54	-0.54	-1.51
GDP_{t-1}, PMI, TS, CISS	0.18	0.05	-0.26	-1.01	-1.05	-1.52
Full model and TS	0.28	0.12	-0.26	-1.13	-1.24	-1.42
Benchmark full model	0.42	0.24	-0.16	-1.04	-1.14	-1.27
Predictive Score						
GDP_{t-1}, PMI	0.04	0.04	0.04	0.24	0.21	
GDP_{t-1}, PMI, TS	0.07	0.06	0.05	0.31	0.31	
GDP_{t-1}, PMI, TS, CISS	0.02	0.05	0.37	0.34	0.31	
Full model with TS	0.00	0.06	0.23	0.52	0.52	
Benchmark full model	0.00	0.02	0.18	0.48	0.51	

Notes: This table shows the absolute prediction error with respect to the mean of the predictive distribution and the predictive score. The former is defined as the absolute value of the difference between the revised data on GDP growth and the mean of the real-time predictive distributions of GDP growth. The latter is the predictive distribution evaluated at the realized value of the time series. Lower absolute prediction errors and higher predictive scores indicate more accurate predictions. ([1]) GDP growth one quarter ahead is measured as quarterly log difference, y_{t+1}. GDP growth one-year ahead is defined as $y_{t+4} = \frac{1}{4}\sum_{h=1}^{4} y_{t+h}$ (i.e. year-on-year quarterly real GDP growth). ([a]) Prediction for q-o-q growth rate in 2020Q1. ([b]) Prediction for q-o-q growth rate in 2020Q2.

Table 11: Great & Covid-19 Recessions - Mean Squared Forecast Errors with Term Spread

	One-quarter ahead			*One-year ahead*		
	Median	Mean	Mode	Median	Mean	Mode
Panel A: Great Recession						
GDP_{t-1}, PMI	1.00	0.98	1.02	1.57	1.45	1.69
GDP_{t-1}, PMI, TS	1.07	1.13	1.00	1.68	1.73	1.64
GDP_{t-1}, PMI, TS, CISS	0.64	0.77	0.58	1.19	1.16	1.22
Full model with TS	0.42	0.33	0.56	0.69	0.69	0.73
Benchmark full model	0.26	0.18	0.97	0.70	0.68	0.84
Panel B: Covid-19 Recession						
GDP_{t-1}, PMI	1.37	1.47	1.32			
GDP_{t-1}, PMI, TS	1.17	1.22	1.14			
GDP_{t-1}, PMI, TS, CISS	0.81	0.92	1.16			
Full model with TS	0.98	1.01	0.94			
Benchmark full model	1.20	1.20	1.19			

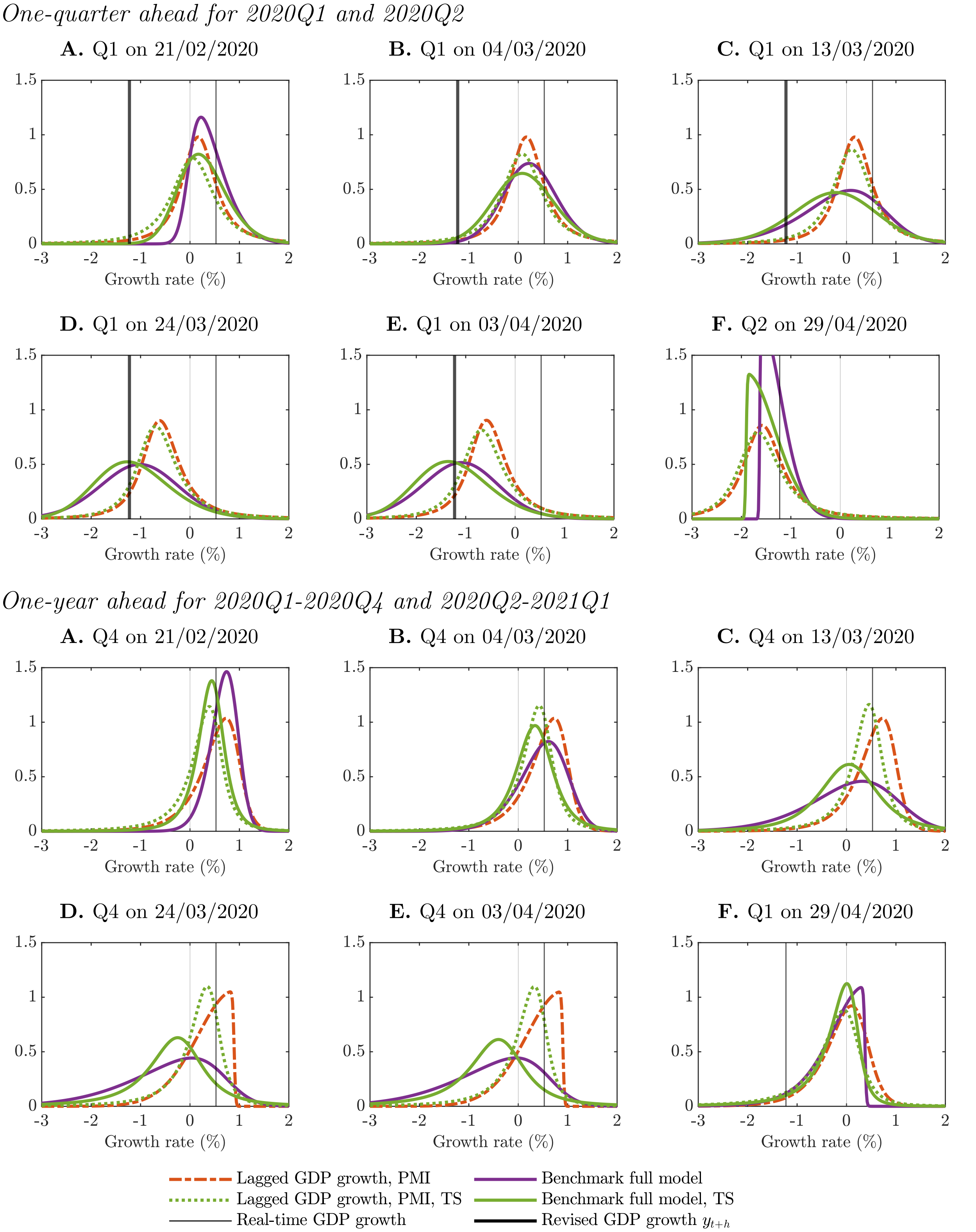
Notes: This table shows the MSFE computed as the average of the squared difference between the revised data on GDP growth and (i) the median, (ii) the mean, and (iii) the mode of the real-time predictive distributions of GDP growth.

indicators, such as the flash estimate of the Markit Purchasing Managers Index (PMI), the scope for financial markets to provide timely forecasts becomes even more challenging.

By employing out-of-sample forecast performance metrics and summary statistics to estimate the donwside risk, we show that financial variables contribute to the real-time forecast of GDP growth and its associated risk during the Great Recession and the Covid-19 Recession after controlling for macroeconomic variables. They provide additional insights on both the first and the higher moments of the GDP growth distribution. In the case of the Great Recession, the full model with financial variables suggests a fall in economic growth and a considerable macroeconomic risk already at the end of 2007. In the case of the Covid-19 pandemic crisis, financial variables have served policymakers at the beginning of March 2020, providing timely warnings about the severity of the crisis and the significant downside risk, well before the publication of macroeconomic releases.

The literature showing the relationship between monetary policy and financial variables has been recently growing. Cúrdia and Woodford (2010), Gambacorta and Signoretti (2014) and Adrian et al. (2020) propose models with Taylor rules augmented with financial variables. Caldara and Herbst (2019) show that the systematic component of monetary policy is function of changes in corporate credit spreads. Adrian and Liang (2018) show that the Taylor rules augmented by financial variables are characterised by a trade off between current macroeconomic objectives and future risks, where financial variables measure GDP vulnerability. The results of this paper corroborate the view of this strand of the literature.

Figure 9: Term Spread - Probability Densities of GDP Growth during the Covid-19 Recession



Notes: Each panel shows the skew-t probability densities for four different models and the predictive quantiles for the full model. 'Full model' refers to the model that includes lagged GDP growth, PMI, CISS and corporate spreads of non-financial corporations. The title of each panel indicates the real-time date of the forecast and the predicted quarter(s). The predictions for GDP growth one-year ahead predict the quarterly year-on-year growth rate. GDP growth one-year ahead is defined as $y_{t+4} = \frac{1}{4}\sum_{h=1}^{4} y_{t+h}$ (i.e. year-on-year quarterly real GDP growth).

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Appendix

Table A1: Great Recession - Macroeconomic Risk using other Macro Variables

	One-quarter ahead						*One-year ahead*					
	07Q4	08Q1	08Q2	08Q3	08Q4	09Q1	08Q3	08Q4	09Q1	09Q2	09Q3	09Q4
5% Shortfall												
GDP_{t-1}, ISM	-1.04	-1.29	-1.28	-1.10	-2.73	-2.87	-0.70	-1.39	-1.38	-0.95	-1.24	-1.81
Full model with ISM	-2.27	-3.44	-2.49	-3.25	-7.12	-4.66	-0.82	-1.16	-0.68	-0.56	-1.60	-1.32
GDP_{t-1}, CBLI	-0.03	-0.45	-0.42	-0.38	-0.63	-1.77	-0.09	0.24	0.23	0.08	0.18	0.18
Full model with CBLI	-1.69	-2.65	-1.47	-1.52	-5.09	-3.69	0.07	-0.20	0.08	-0.01	-1.06	-1.13
GDP_{t-1}, CFNAI	-0.88	-1.49	-1.58	-1.27	-1.72	-3.48	-0.46	-0.79	-0.77	-0.61	-0.86	-1.54
Full model with CFNAI	-2.16	-2.79	-1.70	-0.55	-3.10	-1.67	-1.80	-3.00	-1.72	-1.50	-1.55	-2.64
Benchmark full model	-2.28	-3.38	-2.12	-2.17	-5.58	-4.55	-0.80	-1.08	-0.63	-0.46	-1.52	-1.26
Upside Entropy												
GDP_{t-1}, ISM	-0.06	-0.11	-0.11	-0.07	0.21	0.39	-0.02	-0.10	-0.06	-0.03	-0.14	-0.10
Full model with ISM	-0.14	-0.20	-0.14	-0.14	0.62	1.62	-0.19	-0.09	-0.12	-0.03	0.52	0.52
GDP_{t-1}, CBLI	0.13	0.07	0.06	0.02	0.02	0.29	0.49	0.58	0.62	0.43	0.65	0.78
Full model with CBLI	-0.20	-0.12	-0.10	-0.11	0.69	1.65	0.27	0.73	0.38	0.15	0.91	0.81
GDP_{t-1}, CFNAI	-0.05	0.02	0.00	-0.05	0.02	0.81	-0.08	-0.17	-0.16	-0.13	-0.14	0.15
Full model with CFNAI	-0.06	-0.15	-0.04	-0.08	0.58	0.72	-0.12	-0.15	-0.04	0.11	0.00	0.41
Benchmark full model	-0.16	-0.12	-0.06	0.02	1.32	1.76	-0.19	-0.06	-0.11	0.06	0.65	0.62
Downside Entropy												
GDP_{t-1}, ISM	0.10	0.23	0.22	0.11	0.83	0.93	0.05	0.14	0.11	0.04	0.35	0.42
Full model with ISM	0.32	0.62	0.46	0.30	1.33	1.38	0.57	1.05	0.64	0.60	2.02	1.84
GDP_{t-1}, CBLI	0.08	0.37	0.33	0.11	0.42	0.75	0.16	0.43	0.38	0.24	0.42	1.00
Full model with CBLI	0.54	0.95	0.69	0.51	1.46	1.59	1.12	1.52	1.14	1.08	2.18	1.99
GDP_{t-1}, CFNAI	0.24	0.67	0.62	0.47	0.68	1.49	0.16	0.48	0.39	0.27	0.37	1.15
Full model with CFNAI	0.08	0.49	0.54	0.31	-0.20	1.74	0.21	0.50	0.39	0.28	0.62	1.36
Benchmark full model	0.36	0.75	0.49	0.56	1.47	1.47	0.59	1.12	0.67	0.67	2.10	1.91
Probability of Contraction												
GDP_{t-1}, ISM	11	17	17	13	65	79	8	10	9	9	18	21
Full model with ISM	33	46	35	26	92	100	25	52	26	21	86	86
GDP_{t-1}, CBLI	2	5	4	5	8	52	2	0	0	1	0	0
Full model with CBLI	41	63	47	36	94	100	0	51	0	4	92	92
GDP_{t-1}, CFNAI	11	46	40	26	46	95	9	20	18	13	21	68
Full model with CFNAI	14	37	31	15	11	94	12	26	20	11	28	81
Benchmark full model	34	53	37	41	100	100	26	55	27	20	88	88
Expected Value in case of Contraction												
GDP_{t-1}, ISM	-0.55	-0.54	-0.54	-0.55	-0.61	-0.65	-0.46	-0.80	-0.81	-0.60	-0.50	-0.64
Full model with ISM	-0.86	-1.17	-0.75	-1.00	-1.62	-1.42	-0.35	-0.50	-0.29	-0.25	-0.97	-0.83
GDP_{t-1}, CBLI	-0.42	-0.47	-0.47	-0.42	-0.41	-0.41	-0.66	-0.07	-0.10	-0.38	-0.08	0.04
Full model with CBLI	-0.67	-1.00	-0.54	-0.57	-1.68	-1.70	0.04	-0.11	0.05	-0.01	-0.76	-0.77
GDP_{t-1}, CFNAI	-0.46	-0.46	-0.47	-0.44	-0.49	-1.41	-0.30	-0.35	-0.35	-0.32	-0.37	-0.60
Full model with CFNAI	-0.94	-0.75	-0.49	-0.27	-1.64	-1.06	-0.86	-0.92	-0.65	-0.76	-0.47	-0.89
Benchmark full model	-0.86	-1.17	-0.71	-0.69	-1.68	-1.53	-0.34	-0.49	-0.27	-0.21	-0.97	-0.83

Notes: This table summarises the macroeconomic risk in economic activity using five indicators. The 5% expected shortfall measures the expected value in the lower 5% tail of the conditional probability density. The downside entropy measures the conditional risks to the downside in excess of the downside risks predicted by the unconditional distribution, evaluated over the entire 50% left tail of the conditional distribution. The upside entropy measures the conditional risks to the upside in excess of the upside risks predicted by the unconditional distribution, evaluated over the entire 50% right tail of the conditional distribution. The probability of a contraction is the CDF evaluated at zero growth rate. The expected severity of contraction is the expected value conditional on a contraction. GDP growth one-year ahead is defined as $y_{t+4} = \frac{1}{4}\sum_{h=1}^{4} y_{t+h}$ (i.e. year-on-year quarterly real GDP growth).

Table A2: Great Recession - Absolute Prediction Errors using other Macro Variables

	One-quarter ahead						*One-year ahead*					
	07Q4	08Q1	08Q2	08Q3	08Q4	09Q1	07Q4	08Q1	08Q2	08Q3	08Q4	09Q1
Revised GDP growth[1]	0.61	-0.57	0.52	-0.54	-2.16	-1.12	0.00	-0.69	-0.83	-0.99	-0.77	0.05
Absolute Prediction Error w.r.t. Median of the Predictive Distribution												
GDP_{t-1}, ISM	0.09	1.10	0.02	1.19	2.02	0.79	0.78	1.39	1.54	1.76	1.23	0.34
Full model with ISM	0.13	0.69	0.26	0.97	1.10	0.02	0.39	0.66	1.13	1.33	0.15	0.84
GDP_{t-1}, CBLI	0.29	1.11	0.04	1.27	2.62	1.11	0.81	1.34	1.50	1.74	1.36	0.32
Full model with CBLI	0.38	0.22	0.46	0.78	0.91	0.40	0.29	0.69	1.10	1.23	0.03	0.84
GDP_{t-1}, CFNAI	0.05	0.63	0.40	0.83	2.23	0.16	0.71	1.16	1.32	1.58	1.22	0.32
Full model with CFNAI	0.09	0.78	0.31	1.04	3.49	0.04	0.64	1.09	1.30	1.55	1.00	0.63
Benchmark full model	0.18	0.50	0.27	0.70	0.85	0.14	0.38	0.61	1.11	1.29	0.19	0.87
Absolute Prediction Error w.r.t. Mean of the Predictive Distribution												
GDP_{t-1}, ISM	0.09	1.07	0.01	1.18	1.95	0.70	0.72	1.33	1.47	1.70	1.19	0.31
Full model with ISM	0.28	0.43	0.38	0.78	0.70	0.32	0.40	0.77	1.14	1.31	0.03	0.65
GDP_{t-1}, CBLI	0.31	1.14	0.07	1.28	2.66	1.07	0.75	1.31	1.46	1.69	1.33	0.32
Full model with CBLI	0.34	0.21	0.49	0.69	0.62	0.57	0.34	0.73	1.14	1.30	0.17	0.69
GDP_{t-1}, CFNAI	0.07	0.61	0.43	0.80	2.20	0.18	0.66	1.12	1.28	1.53	1.17	0.32
Full model with CFNAI	0.02	0.81	0.30	1.03	3.24	0.15	0.54	0.92	1.14	1.41	0.99	0.70
Benchmark full model	0.36	0.25	0.44	0.53	0.50	0.42	0.40	0.73	1.13	1.29	0.01	0.67

Notes: This table shows the absolute prediction error with respect to the mean of the predictive distribution and the predictive score. The former is defined as the absolute value of the difference between the revised data on GDP growth and the mean of the real-time predictive distributions of GDP growth. The latter is the predictive distribution evaluated at the realized value of the time series. Lower absolute prediction errors and higher predictive scores indicate more accurate predictions. ([1]) GDP growth one quarter ahead is measured as quarterly log difference, y_{t+1}. GDP growth one-year ahead is defined as $y_{t+4} = \frac{1}{4}\sum_{h=1}^{4} y_{t+h}$ (i.e. year-on-year quarterly real GDP growth).

Table A3: Great Recession - Macroeconomic Risk using Term Spread

	One-quarter ahead						*One-year ahead*					
	07Q4	08Q1	08Q2	08Q3	08Q4	09Q1	08Q3	08Q4	09Q1	09Q2	09Q3	09Q4
5% Shortfall												
GDP_{t-1}, PMI	-0.76	-1.21	-1.11	-1.21	-2.51	-2.66	-0.91	-1.07	-1.04	-1.01	-1.23	-1.75
GDP_{t-1}, PMI, TS	-0.88	-0.71	-0.58	-0.80	-1.13	-2.14	-0.29	-0.22	-0.14	-0.30	-0.48	-0.94
GDP_{t-1}, PMI, TS, CISS	-1.47	-2.14	-1.00	-0.96	-4.38	-3.98	-1.19	-1.89	-1.10	-0.89	-3.08	-2.65
Full model with TS	-1.55	-1.87	-0.95	-0.92	-4.00	-3.04	-1.17	-1.45	-0.87	-0.87	-0.98	-0.96
Benchmark full model	-2.35	-3.25	-1.84	-2.02	-5.64	-9.93	-0.75	-0.91	-0.57	-0.38	-1.40	-1.16
Upside Entropy												
GDP_{t-1}, PMI	-0.09	-0.13	-0.13	-0.15	0.24	0.42	-0.01	-0.13	-0.09	-0.07	-0.14	-0.09
GDP_{t-1}, PMI, TS	-0.14	-0.12	-0.12	-0.15	0.21	0.47	-0.10	-0.10	-0.05	-0.05	0.01	-0.07
GDP_{t-1}, PMI, TS, CISS	-0.12	-0.15	-0.18	-0.19	0.10	0.23	-0.16	-0.15	-0.09	-0.11	-0.08	-0.02
Full model with TS	-0.20	-0.17	-0.10	0.01	1.65	1.98	0.02	0.13	0.05	0.18	0.97	0.88
Benchmark full model	-0.16	-0.12	-0.06	0.02	1.32	1.76	-0.19	-0.06	-0.11	0.06	0.65	0.62
Downside entropy												
GDP_{t-1}, PMI	0.17	0.37	0.29	0.36	0.93	1.00	0.02	0.19	0.12	0.08	0.33	0.49
GDP_{t-1}, PMI, TS	0.29	0.40	0.30	0.43	1.01	0.96	0.23	0.20	0.14	0.13	0.15	0.33
GDP_{t-1}, PMI, TS, CISS	0.32	0.41	0.41	0.49	1.18	1.16	0.36	0.43	0.23	0.18	0.78	0.82
Full model with TS	0.47	0.68	0.49	0.62	1.38	1.52	0.73	0.95	0.63	0.68	2.19	2.06
Benchmark full model	0.36	0.75	0.49	0.56	1.47	1.47	0.59	1.12	0.67	0.67	2.10	1.91
Probability of Contraction												
GDP_{t-1}, PMI	14	24	20	24	72	82	8	11	10	10	17	24
GDP_{t-1}, PMI, TS	20	20	15	24	68	80	6	3	3	4	4	10
GDP_{t-1}, PMI, TS, CISS	31	37	29	32	75	81	15	19	10	10	43	49
Full model with TS	37	49	29	32	100	100	24	46	16	15	93	92
Benchmark full model	33	56	47	40	100	100	28	61	30	22	93	93
Expected Value in case of Contraction												
GDP_{t-1}, PMI	-0.37	-0.46	-0.45	-0.46	-0.60	-0.67	-0.63	-0.57	-0.58	-0.60	-0.51	-0.57
GDP_{t-1}, PMI, TS	-0.38	-0.31	-0.28	-0.33	-0.40	-0.52	-0.23	-0.34	-0.34	-0.39	-0.59	-0.52
GDP_{t-1}, PMI, TS, CISS	-0.60	-0.82	-0.42	-0.38	-1.28	-1.15	-0.53	-0.70	-0.63	-0.50	-0.78	-0.66
Full model with TS	-0.61	-0.69	-0.37	-0.32	-1.21	-1.25	-0.38	-0.38	-0.36	-0.36	-0.71	-0.69
Benchmark full model	-0.86	-1.17	-0.71	-0.69	-1.68	-1.53	-0.34	-0.49	-0.27	-0.21	-0.97	-0.83

Notes: This table summarises the macroeconomic risk in economic activity using five indicators. The 5% expected shortfall measures the expected value in the lower 5% tail of the conditional probability density. The downside entropy measures the conditional risks to the downside in excess of the downside risks predicted by the unconditional distribution, evaluated over the entire 50% left tail of the conditional distribution. The upside entropy measures the conditional risks to the upside in excess of the upside risks predicted by the unconditional distribution, evaluated over the entire 50% right tail of the conditional distribution. The probability of a contraction is the CDF evaluated at zero growth rate. The expected severity of contraction is the expected value conditional on a contraction. GDP growth one-year ahead is defined as $y_{t+4} = \frac{1}{4}\sum_{h=1}^{4} y_{t+h}$ (i.e. year-on-year quarterly real GDP growth).

Table A4: Covid-19 Recession - Macroeconomic Risk using Term Spread

	One-quarter ahead						*One-year ahead*					
	21/2[a]	04/3[a]	13/3[a]	24/3[a]	03/4[a]	23/4[b]	21/2[c]	04/3[c]	13/3[c]	24/3[c]	03/4[c]	23/4[d]
5% Shortfall												
GDP_{t-1}, PMI	-1.66	-1.66	-1.66	-2.35	-2.32	-3.57	-0.96	-0.97	-0.97	-0.96	-0.95	-1.54
GDP_{t-1}, PMI, TS	-2.44	-2.27	-2.11	-2.46	-2.58	-3.59	-2.21	-2.02	-1.84	-2.56	-2.68	-3.72
GDP_{t-1}, PMI, TS, CISS	-0.97	-1.15	-1.86	-2.44	-2.59	-2.06	-0.29	-0.96	-2.25	-3.35	-3.53	-2.87
Full model with TS	-0.67	-1.16	-2.13	-2.64	-2.76	-1.89	-0.74	-1.22	-2.30	-3.99	-4.32	-3.22
Benchmark full model	-0.20	-0.90	-2.22	-2.79	-2.86	-1.62	-0.01	-0.78	-2.23	-2.97	-3.08	-1.77
Upside Entropy												
GDP_{t-1}, PMI	-0.07	-0.07	-0.07	0.37	0.35	1.03	-0.07	-0.07	-0.07	0.07	0.07	0.20
GDP_{t-1}, PMI, TS	-0.08	-0.08	-0.08	0.38	0.35	0.97	0.00	-0.03	-0.05	0.03	0.06	0.30
GDP_{t-1}, PMI, TS, CISS	0.01	-0.10	-0.12	0.23	0.21	1.22	0.00	-0.11	-0.15	-0.11	-0.07	0.29
Full model with TS	-0.13	-0.15	-0.11	0.59	0.69	1.32	0.00	-0.10	-0.11	0.13	0.25	0.45
Benchmark full model	-0.08	-0.13	-0.15	0.52	0.64	1.43	0.05	-0.14	-0.22	-0.06	0.02	0.60
Downside entropy												
GDP_{t-1}, PMI	0.52	0.53	0.53	1.18	1.15	1.68	0.16	0.16	0.16	0.40	0.39	0.82
GDP_{t-1}, PMI, TS	0.62	0.60	0.58	1.22	1.20	1.71	0.46	0.41	0.36	0.53	0.56	0.96
GDP_{t-1}, PMI, TS, CISS	0.60	0.77	1.10	1.72	1.73	2.31	0.48	0.51	0.78	0.96	1.03	0.96
Full model with TS	0.54	0.63	0.90	1.55	1.60	2.10	0.39	0.46	0.75	1.07	1.20	0.91
Benchmark full model	0.52	0.52	0.76	1.44	1.48	2.13	0.14	0.26	0.72	1.11	1.19	0.92
Probability of Contraction												
GDP_{t-1}, PMI	33	33	33	84	83	96	14	14	14	24	24	52
GDP_{t-1}, PMI, TS	46	43	41	85	84	95	25	22	19	30	32	67
GDP_{t-1}, PMI, TS, CISS	32	52	65	82	82	97	11	27	49	58	61	67
Full model with TS	30	43	61	92	94	100	12	24	48	69	76	65
Benchmark full model	12	34	54	90	93	100	2	18	45	63	67	61
Expected Value in case of Contraction												
GDP_{t-1}, PMI	-0.47	-0.47	-0.47	-0.75	-0.73	-1.62	-0.47	-0.47	-0.47	-0.40	-0.40	-0.48
GDP_{t-1}, PMI, TS	-0.61	-0.58	-0.55	-0.82	-0.83	-1.67	-0.69	-0.68	-0.68	-0.72	-0.72	-0.76
GDP_{t-1}, PMI, TS, CISS	-0.32	-0.44	-0.86	-1.44	-1.51	-1.64	-0.16	-0.36	-0.71	-0.96	-1.01	-0.62
Full model with TS	-0.28	-0.45	-0.79	-1.27	-1.35	-1.43	-0.37	-0.44	-0.66	-0.90	-0.98	-0.64
Benchmark full model	-0.11	-0.36	-0.78	-1.20	-1.25	-1.28	-0.15	-0.36	-0.80	-1.01	-1.04	-0.54

Notes: This table summarises the macroeconomic risk in economic activity using five indicators. The 5% expected shortfall measures the expected value in the lower 5% tail of the conditional probability density. The downside entropy measures the conditional risks to the downside in excess of the downside risks predicted by the unconditional distribution, evaluated over the entire 50% left tail of the conditional distribution. The upside entropy measures the conditional risks to the upside in excess of the upside risks predicted by the unconditional distribution, evaluated over the entire 50% right tail of the conditional distribution. The probability of a contraction is the CDF evaluated at zero growth rate. The expected severity of contraction is the expected value conditional on a contraction. GDP growth one-year ahead is defined as $y_{t+4} = \frac{1}{4}\sum_{h=1}^{4} y_{t+h}$ (i.e. year-on-year quarterly real GDP growth). (^{a}) Prediction for q-o-q growth rate in 2020Q1. (^{b}) Prediction for q-o-q growth rate in 2020Q2. (^{c}) Prediction for q-o-q annual growth rate from 2020Q1 to 2020Q4. (^{d}) Prediction for q-o-q annual growth rate from 2020Q2 to 2021Q1.

Table A5: Great Recession & Covid-19 - Absolute Prediction Errors with Term Spread

	One-quarter ahead						*One-year ahead*					
Panel A: Great Recession												
	07Q4	08Q1	08Q2	08Q3	08Q4	09Q1	07Q4	08Q1	08Q2	08Q3	08Q4	09Q1
Revised GDP growth[1]	0.61	-0.57	0.52	-0.54	-2.16	-1.12	0.00	-0.69	-0.83	-0.99	-0.77	0.05
Absolute Prediction Error w.r.t. Median of the Predictive Distribution												
GDP_{t-1}, PMI	0.03	0.96	0.04	0.94	1.92	0.72	0.81	1.36	1.53	1.72	1.25	0.28
GDP_{t-1}, PMI, TS	0.10	0.98	0.01	0.90	1.98	0.83	0.67	1.39	1.56	1.71	1.46	0.45
GDP_{t-1}, PMI, TS, CISS	0.12	0.95	0.13	0.84	1.45	0.35	0.53	1.16	1.44	1.63	0.89	0.04
Full model with TS	0.31	0.60	0.23	0.72	1.22	0.03	0.24	0.73	1.14	1.28	0.02	0.77
Benchmark full model	0.18	0.50	0.27	0.70	0.85	0.14	0.38	0.61	1.11	1.29	0.19	0.87
Absolute Prediction Error w.r.t. Mean of the Predictive Distribution												
GDP_{t-1}, PMI	0.04	0.95	0.05	0.94	1.90	0.67	0.73	1.31	1.47	1.65	1.21	0.27
GDP_{t-1}, PMI, TS	0.05	1.00	0.00	0.95	2.07	0.79	0.65	1.43	1.61	1.72	1.47	0.47
GDP_{t-1}, PMI, TS, CISS	0.09	0.92	0.09	0.93	1.64	0.44	0.49	1.14	1.46	1.61	0.85	0.01
Full model and TS	0.31	0.58	0.24	0.74	0.96	0.13	0.29	0.81	1.17	1.27	0.19	0.60
Benchmark full model	0.36	0.25	0.44	0.53	0.50	0.42	0.40	0.73	1.13	1.29	0.01	0.67
Panel B: Covid-19 Recession												
	21/2[a]	04/3[a]	13/3[a]	24/3[a]	03/4[a]							
Revised GDP growth[1]	-1.23	-1.23	-1.23	-1.23	-1.23							
Absolute Prediction Error w.r.t. Median of the Predictive Distribution												
GDP_{t-1}, PMI	1.41	1.41	1.41	0.66	0.69							
GDP_{t-1}, PMI, TS	1.28	1.31	1.33	0.59	0.60							
GDP_{t-1}, PMI, TS, CISS	1.39	1.20	0.80	0.06	0.10							
Full model with TS	1.47	1.33	0.98	0.05	0.05							
Benchmark full model	1.58	1.45	1.15	0.19	0.11							
Absolute Prediction Error w.r.t. Mean of the Predictive Distribution												
GDP_{t-1}, PMI	1.44	1.44	1.44	0.74	0.77							
GDP_{t-1}, PMI, TS	1.28	1.31	1.34	0.69	0.69							
GDP_{t-1}, PMI, TS, CISS	1.41	1.27	0.97	0.21	0.17							
Full model and TS	1.51	1.35	0.97	0.10	0.01							
Benchmark full model	1.64	1.46	1.07	0.18	0.09							

Notes: This table shows the absolute prediction error with respect to the mean of the predictive distribution and the predictive score. The former is defined as the absolute value of the difference between the revised data on GDP growth and the mean of the real-time predictive distributions of GDP growth. The latter is the predictive distribution evaluated at the realized value of the time series. Lower absolute prediction errors and higher predictive scores indicate more accurate predictions. ([1]) GDP growth one quarter ahead is measured as quarterly log difference, y_{t+1}. GDP growth one-year ahead is defined as $y_{t+4} = \frac{1}{4}\sum_{h=1}^{4} y_{t+h}$ (i.e. year-on-year quarterly real GDP growth). ([a]) Prediction for q-o-q growth rate in 2020Q1.

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