

Financial Variables as Predictors of Real Growth Vulnerability

Lucrezia Reichlin¹, Giovanni Ricco², and Thomas Hasenzagl³

¹*London Business School, Now-Casting Economics, and CEPR*

²*University of Warwick and OFCE-SciencesPo, and CEPR*

³*University of Minnesota*

First draft: 16 June 2019

This version: 30th October 2019

Abstract

We evaluate the role of financial conditions as predictors of macroeconomic risk first in the quantile regression framework of [Adrian et al. \(2019b\)](#), which allows for non-linearities, and then in a novel linear semi-structural model as proposed by [Hasenzagl et al. \(2018\)](#). We distinguish between price variables such as credit spreads and stock variables such as leverage. We find that (i) although the spreads correlate with the left tail of the conditional distribution of GDP growth, they provide limited advanced information on growth vulnerability; (ii) nonfinancial leverage provides a leading signal for the left quantile of the GDP growth distribution in the 2008 recession; (iii) measures of excess leverage conceptually similar to the Basel gap, but cleaned from business cycle dynamics via the lenses of the semi-structural model, point to two peaks of accumulation of risks – the eighties and the first eight years of the new millennium, with an unstable relationship with business cycle chronology.

Keywords: financial cycle, business cycle, credit, financial crises, downside risk, entropy, quantile regressions.

JEL Classification: E32, E44, C32, C53.

This paper has been prepared for the 5th Annual Macroprudential Conference in Eltville organised by the Deutsche Bundesbank, the Sveriges Riksbank and De Nederlandsche Bank. We are grateful to Domenico Giannone for sharing the codes of [Adrian et al. \(2019b\)](#), and for many helpful suggestions and comments. We also acknowledge Vítor Constâncio's and Mikkel Plagborg-Møller's very insightful discussions of a preliminary version of this work. We thank Juan Antolin Diaz, Andrea Carriero, Simone Manganeli, Filippo Pellegrino, Ivan Petrella, Hélène Rey and participants at the 5th Annual Macroprudential Conference for many helpful comments.

Introduction

Following the Great Recession, there has been an increasing interest in understanding the relation between financial fragility and the business cycle. Beyond academic research, many policy institutions have developed empirical models to identify early signals of financial crises and subsequent large output losses (see, for example, [Lang et al., 2019](#) for recent work at the European Central Bank) in a revisitation of the literature of the 1990s on early warning indicators for currency crises (see [Kaminsky, 1999](#), as a classic reference).

The large body of literature on the macro-financial interactions in recessions has traditionally found few robust results on the predictability of real economic activity using financial predictors (see, for example, [Stock and Watson, 2003](#), [Forni et al., 2003](#) and [Hatzius et al., 2010](#)). This may have different explanations: for example, financial innovation may cause some financial indicators to lose or acquire predictive power over time, or the relation between financial and real variables may be nonlinear so that financial variables' predictive power is activated during extreme events as many macro-finance models indeed suggest (see [Gertler and Gilchrist, 2018](#)'s survey).

For this reason, recently, there has been a renewed effort to develop new methods for assessing the risk of large output losses, given financial conditions, rather than focusing exclusively on the prediction of the mean. In a recent seminal contribution, [Adrian et al. \(2019b\)](#) have pioneered this research and suggested an easily implementable method for this purpose. Focusing on US data, they have found that the lower quantiles of GDP growth vary with financial conditions while the upper quantiles are stable over time, therefore pointing to an asymmetric and non-linear relationship between financial and real variables. [Adrian et al. \(2018\)](#) have confirmed this result extending the sample to different countries and have pushed this view further by defining the concept of growth at risk as GDP growth at the lower fifth percentile of the GDP growth distribution, conditional on an index of financial stress. Building on this work, several recent papers have explored the idea, while policy institutions have adopted the methodology to monitor risk in different countries (see, for example, [Prasad et al., 2019](#) for a description of the use of this method at the IMF). The appeal of this approach to policy work is that it provides a framework in which forecasting can be thought of as a risk managing exercise (see [Kilian and Manganelli, 2008](#) for the first development of this idea). This is the core idea of what is referred to as the Growth at Risk (GaR) framework of [Adrian et al. \(2018\)](#).¹

A separate line of research pioneered by the BIS has stressed the importance of the leverage cycle as an indicator of risk, while several studies have pointed at a correlation of excess growth in leverage and financial crisis (see [Jorda et al., 2011](#), [Schularick and Taylor, 2012](#), [Jorda et al., 2013](#) and related literature) and found that recessions preceded by financial crises are deeper and followed by slower recoveries (e.g. [Reinhart and Rogoff, 2009](#), [Laeven and Valencia, 2012](#) and related literature). Empirical work has also identified a financial cycle with different characteristics than the business cycle but related to it, with financial cycle booms either ending-up in crises or weakening growth (see [Borio and Lowe, 2002](#) for early work and more recently [Drehmann](#)

¹Recent contributions to this line of research are in [Adrian et al. \(2019a\)](#), [Loria et al. \(2019\)](#), [Brownlees and Souza \(2019\)](#), [Figueres and Jarociński \(2019\)](#) and [Delle Monache et al. \(2019\)](#).

et al., 2012, Claessens et al., 2012 and many other papers). Based on this evidence, the Basel Committee for Banking Supervision has proposed the use of a credit gap measure as an indicator of excessive credit and increasing vulnerability to banking crises (Basel Committee for Banking Supervision, 2010) where the gap is defined as the difference between the credit to GDP ratio and its trend extracted by a Hodrick-Prescott (HP) filter.

In order to bridge the gap between these two different approaches – both influential in policy institutions – we follow two different modelling strategies. In the first part of the paper, we provide a partial appraisal of the empirical reliability of the risk management approach to macroeconomic forecasting using the US quarterly data from 1973q1 to 2015q1, as a case study. In doing this, we focus on different indicators, reflecting different aspects of financial conditions. First, as in Adrian et al. (2019b), we consider the Chicago Fed’s National Financial Conditions Index (NFCI), aggregating a large set of variables capturing the effect of credit quality, risk and leverage. Second, we consider the household and business nonfinancial leverage component. The NFCI, which aggregates more than one hundred variables, tends to follow closely the dynamic pattern of financial spreads characterised by occasional spikes in coincidence with recessions. The index, therefore, reflects sudden shifts of market expectations possibly providing some near-horizon advanced information on the sudden activation of financial friction and the related deterioration of real economic conditions. Conversely, nonfinancial leverage captures the slow accumulation of the stock of debt in the economy following a smooth dynamic pattern. Therefore, arguably, this variable may provide medium-term information to monitor the building-up of systemic financial instabilities. In the second part of the paper, in order to better understand the joint dynamics of real variables and nonfinancial leverage, we then propose a novel semi-structural time series model able to identify episodes of abnormal credit growth, in the spirit of the credit gap monitored by the Basel Committee for Banking Supervision (2010).²

In the first approach we are interested in assessing the characteristics of the near-horizon predictive distribution of GDP growth, in relation to different aspects of financial conditions. This is with the aim of evaluating the potential of the growth at risk methodology for real time macro-prudential monitoring. In particular, we analyse whether the approach can provide early warning on shifts in the moments of the predictive distribution of GDP growth that may indicate increased vulnerability in the economy. Our second approach aims at identifying excess leverage in credit variables, as deviations of the credit growth from the output trend growth that are not due to the business cycle. This is to provide a tool for medium-horizon monitoring of the building up of financial fragility in the economy.

Our results point to the following stylised facts. First, the NFCI contains little advanced information on recessions beyond what there is already in real economic indicators. As it spikes, reflecting the sharp deterioration of financial conditions in recessions, the variance of the conditional distribution of GDP growth increases while the mean declines (as has been shown by Adrian et al., 2019b) but the increase in variance is driven by the poor predictive performance of the model as shown by the predictive score. Indeed, the NFCI does not help predicting recessions

²The model’s methodology builds on our recent research on inflation (see Hasenzagl et al., 2018) and it is similar in spirit, although not in the specification, to Rünstler and Vlekke (2018) and Lang and Welz (2018).

beyond what can be achieved by lagged GDP only. Second, nonfinancial leverage shows some predictability at least for the last recession driven by an early movement in the left skewness and kurtosis of the predictive distribution. Third, the trend-cycle model reveals that credit variables and macroeconomic variables share a common trend growth component, and that they co-move along the business cycle.

However, they deviate from equilibrium relationships several times and persistently over the sample. These deviations – which we model as autoregressive idiosyncratic drifts in the trend of credit growth – can be used as measures of ‘excess leverage growth’. When cumulating and aggregating across variables we obtain a measure that can be interpreted as ‘excess leverage’, in line with the Basel gap. The model-based measure, however, has more desirable properties than the latter since it is not negatively correlated with GDP growth and it is not affected by business cycle fluctuations.

Our measure points to two phases of excess leverage in our sample – the first in the eighties and the second in the first eight years of the new millennium, before the great recession in 2008. Since then there is a large and persistent correction. Interestingly, the disaggregated analysis points to heterogeneity across sectors. In the eighties, excess leverage involves nonfinancial and financial business but not households. This episode of excess leverage is likely to be due to interaction between Volcker’s disinflation, two severe recessions and depository institutions deregulations which eventually led to the Saving & Loans Institutions and to higher financial leverage. Unlike the non financial business sector, financial businesses do not deleverage until the great recession of 2008 after which there is a large and persistent correction. Households excess leverage starts accumulation in the new millennium and its peak precedes the Great Financial Crisis.

Our conclusion from combining the results of the two models is that there is limited value in financial variables for predicting recessions and, in general, for detecting GDP risk in advance. From the point of view of macro-prudential policy, a more useful exercise is to monitor the joint dynamics of real and financial variables to detect accumulation of financial risk which may lead to crises in the future. Due to strong pro-cyclicality of credit, however, this exercise is non trivial. Moreover, at least in our sample, the relationship between debt accumulation and business cycle chronology appears to be unstable. On balance, our model-based approach for the extraction of an independent growth component in credit is promising and can be extended to consider a more granular analysis of financial markets.

1 Financial Conditions Indicators

The literature studying the relationship between financial stress and business cycle dynamics, as briefly reviewed in the introduction, is large and based on different models and variables. Indeed, different indicators of stress capture different aspects of financial frictions which may be relevant at different moments in time - preceding, contemporaneous and following - the financial crisis (see [Bernanke, 2018](#) for an analysis of the 2008 recession in the US). Moreover, they may have different dynamic characteristics with leverage indicators building up gradually and credit

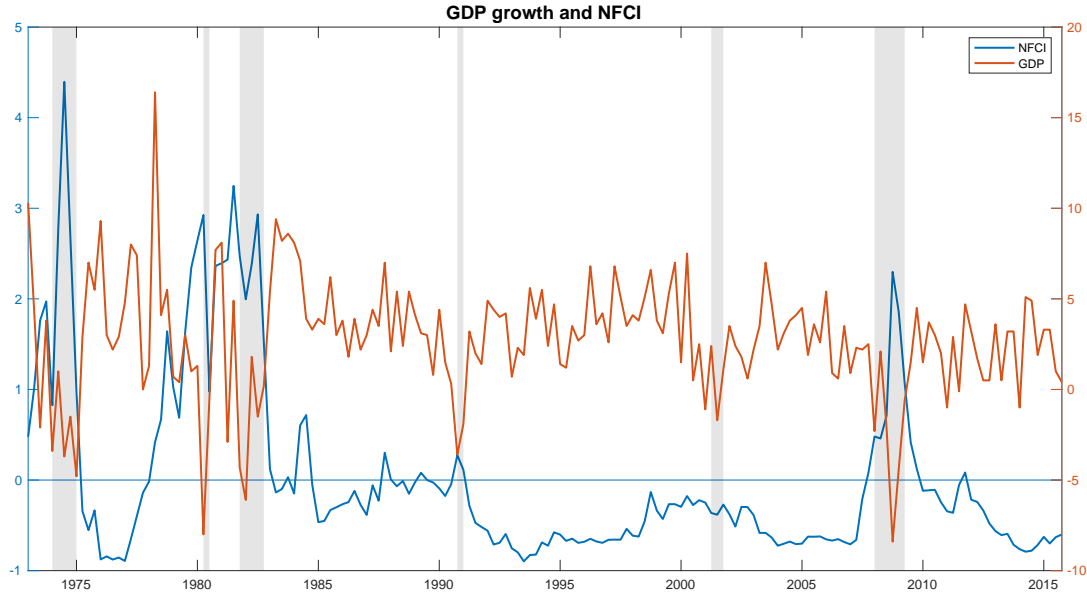


Figure 1: Chicago Fed’s National Financial Condition Index (NFCI) and GDP growth rates for the period from 1973q1 to 2015q1.

spreads spiking up occasionally and suddenly. For example, [Krishnamurthy and Muir \(2017\)](#) have argued that, while leverage signals a gradual build up of financial vulnerability, the interaction between this variable and the sudden shift of market sentiment, as manifested by the spread, explains the severity of the financial crisis.

Let us first consider the Chicago Fed’s National Financial Condition Index (NFCI), aggregated to obtain a quarterly series for the period from 1973q1 to 2015q1. The NFCI is a synthetic indicator computed as a common factor extracted from 105 mixed-frequency – weakly, monthly and quarterly – financial variables, estimated by maximum likelihood as in [Doz et al. \(2012\)](#). The index averages four categories of data: credit quality, risk, non financial and financial leverage. All variables are transformed to stationarity and standardised.³ Figure 1 plots the NFCI against quarterly annualised GDP growth. The chart suggests a negative correlation between the two variables around recessions: the aggregate NFCI spikes up in those episodes roughly at the same time.

Figure 2 provides a more disaggregate view of financial stress by plotting the underlying components of the NFCI against the aggregate index. It shows that the aggregate NFCI dynamics reflects mainly the risk and credit components, while nonfinancial leverage follows a smoother cyclical pattern and financial leverage exhibits some higher frequency idiosyncratic dynamics. This suggests that the NFCI is aggregating components with heterogeneous dynamic characteristics, possibly reflecting different forms of fragility in the financial system.

The nonfinancial leverage subindex is extracted as factor common to two variables only: household debt in home mortgage plus household debt in consumer credit divided by the personal consumption expenditure (PCE) on durables and residential investment and non financial

³For a description of the NFCI (variables considered and methodology), see the Chicago Fed’s dedicated webpage <https://www.chicagofed.org/publications/nfci/index> and [Brave and Butters \(2012\)](#).

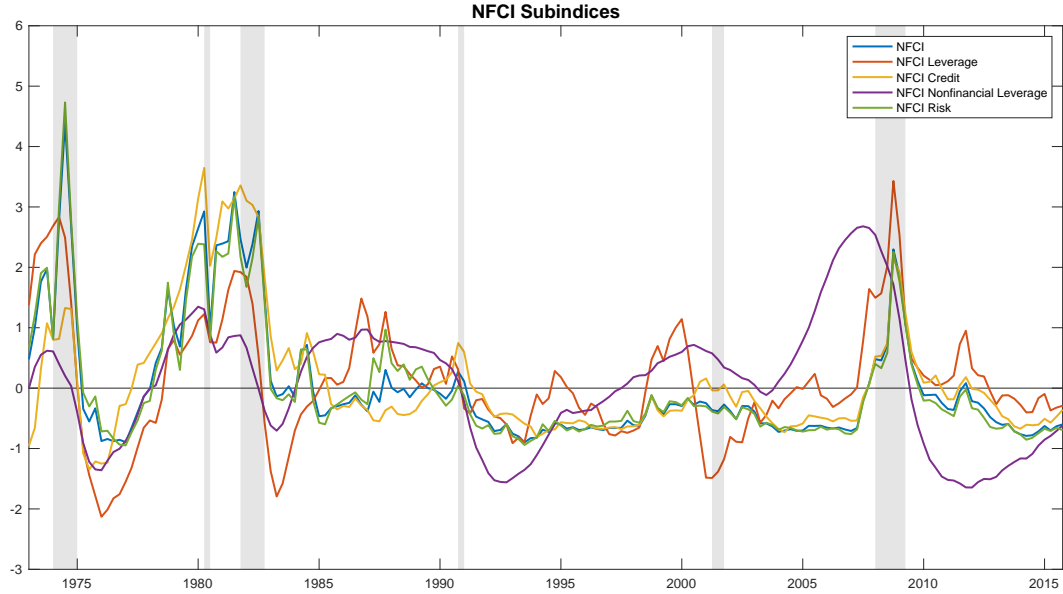


Figure 2: Chicago Fed's National Financial Condition Index (NFCI) underlying components from 1973q1 to 2015q1.

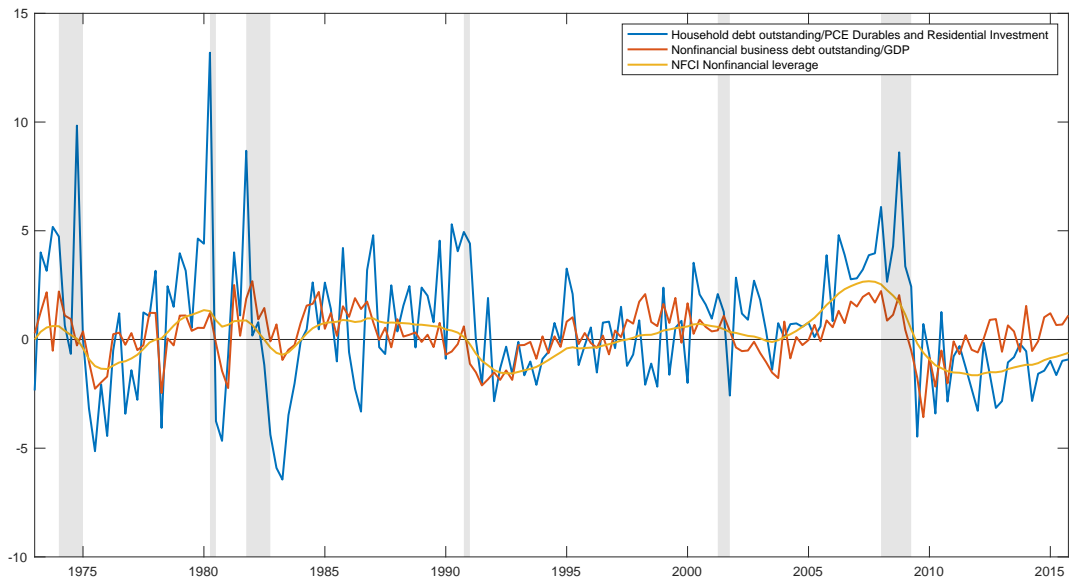


Figure 3: Household debt outstanding/PCE Durables and Residential Investment, Nonfinancial business debt outstanding/GDP (quarter-on-quarter growth rates), and NFCI Nonfinancial Leverage.

business debt divided by nominal GDP ⁴. Figure 3 plots the nonfinancial leverage sub-component of the NFCI and the two variables in quarter-on-quarter rate of growth.

Finally, Figure 4 reports the credit and risk sub-components of the NFCI against a measure of corporate spread. Figure 4 plot them against the detrended value of the Moody Baa corporate bond yield minus the 10-year treasury yield. The chart shows that credit and risk dynamics mimic closely the dynamics of corporate spreads.

⁴The source for the leverage variables is the Federal Reserve Board of Governors.

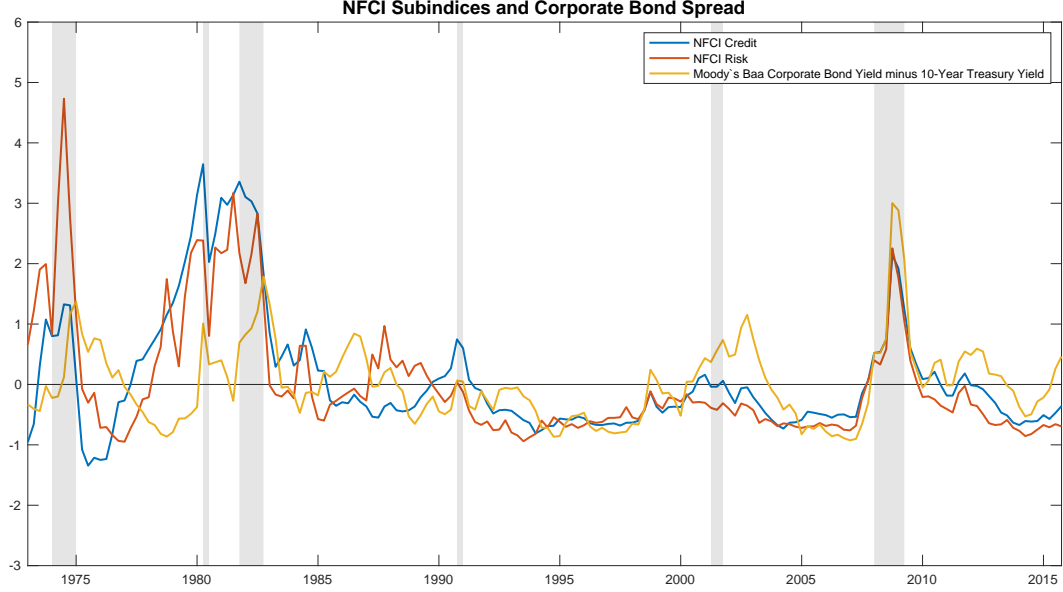


Figure 4: Risk and credit NFCI components and corporate spread

2 A Framework for Growth at Risk

In this section we first introduce the quantile regression framework proposed in the work by [Adrian et al. \(2019b\)](#) to evaluate GDP growth vulnerability and that will be the basis of the first part of our analysis. The first step of the method is to fit a quantile regression using current NFCI, annualised GDP growth and a constant as predictors and annualised average GDP growth as target.

Let us define the annualised average growth rate of GDP between t and $t+h$ as y_{t+h} and the vector of conditioning variables as x_t , including a constant. The conditional quantile function (CQF) of y_{t+h} on x_t at quantile τ is:

$$Q_\tau(y_{t+h}|x_t) = \inf\{y_{t+h} : F_{y_{t+h}}(y_{t+h}|x_t) \geq \tau\}$$

where $F_{y_{t+h}}(y_{t+h}|x_t)$ is the conditional cumulative distribution of y_{t+h} on x_t . The CQF solves the following maximisation problem:

$$Q_\tau(y_{t+h}|x_t) = \operatorname{argmin}_{q(x_t)} \mathbb{E}[\rho_\tau(y_{t+h} - q(x_t))], \quad (1)$$

where $\rho_\tau(u) = (\tau - 1(u \leq 0))u$ is a function which weights positive and negative terms asymmetrically.

Under the assumption that $q(x_t)$ is linear we have

$$\beta_\tau = \operatorname{argmin}_b \mathbb{E}(\rho_\tau(y_{t+h} - x_t' b)). \quad (2)$$

The quantile regression estimator $\hat{\beta}_\tau$ is the sample analog of β_τ and can be found as the solution to a linear programming problem. The sample analog of the CQF at quantile τ is then given by

$$\hat{Q}_\tau(y_{t+h}|x_t) = x_t' \hat{\beta}_\tau. \quad (3)$$

In order to smooth the quantile function and recover a probability density function, we follow [Adrian et al. \(2019b\)](#) and approximate it by fitting the skewed t -distribution developed by [Azzalini and Capitanio \(2003\)](#):

$$f(y; \mu, \sigma, \alpha, \nu) = \frac{2}{\sigma} t\left(\frac{y - \mu}{\sigma}; \nu\right) T\left(\alpha \frac{y - \mu}{\sigma} \sqrt{\frac{\nu + 1}{\nu + \left(\frac{y - \mu}{\sigma}\right)^2}}; \nu + 1\right). \quad (4)$$

This two step methodology is very simple to implement and has been applied widely. The resulting distribution will be characterised by four parameters: $\mu_t, \sigma_t, \alpha_t, \nu_t$ each relating to different moments. The parameters μ and σ describe mean and standard deviation respectively, while α its shape (which determines the skewness) and ν , the degrees of freedom (which determines the kurtosis). When $\alpha = 0$ we have the standard t -distribution; if we also have $\nu = \infty$ the distribution is gaussian while with $\alpha \neq 0$ and $\nu = \infty$ it is a skewed normal. We refer to [Adrian et al. \(2019b\)](#) for details.

Different measures can be adopted to capture the properties of the time varying distribution of GDP growth. We denote by $\hat{g}_{y_{t+h}}$ the (estimated) unconditional density distribution of GDP and by

$$\hat{f}_{y_{t+h}|x_t}(y|x_t) = f(y; \hat{\mu}_{t+h}, \hat{\sigma}_{t+h}, \hat{\alpha}_{t+h}, \hat{\nu}_{t+h})$$

the estimated conditional distribution of GDP, in the form of the estimated skewed t -distribution, i.e. $\hat{f}_{y_t|x_{t-h}}(\bar{y}|x_{t-h})$ for \bar{y} the realised outcome.

The predictive score is computed as the predictive distribution generated by the model and evaluated at the outturn value of the time series. High(er) values of the predictive scores indicate (more) accurate predictions because they show that the model assigns high(er) likelihood to realised outcomes.

The upside, \mathcal{L}_t^U , and downside, \mathcal{L}_t^D , entropy of $\hat{g}_{y_{t+h}}$, relative to $\hat{f}_{y_{t+h}|x_t}(y|x_t)$ are defined as

$$\mathcal{L}_t^D(\hat{f}_{y_{t+h}|x_t}(y|x_t); \hat{g}_{y_{t+h}}) = - \int_{-\infty}^{\hat{F}_{y_{t+h}}^{-1}(0.5|x_t)} \left(\log g_{y_{t+h}}(y) - \log \hat{f}_{y_{t+h}|x_t}(y|x_t) \right) \hat{f}_{y_{t+h}|x_t}(y|x_t) dy$$

$$\mathcal{L}_t^U(\hat{f}_{y_{t+h}|x_t}(y|x_t), \hat{g}_{y_{t+h}}) = - \int_{\hat{F}_{y_{t+h}}^{-1}(0.5|x_t)}^{\infty} \left(\log g_{y_{t+h}}(y) - \log \hat{f}_{y_{t+h}|x_t}(y|x_t) \right) \hat{f}_{y_{t+h}|x_t}(y|x_t) dy$$

where $\hat{F}_{y_{t+h}}^{-1}(y|x_t)$ is the cumulative distribution associated with $\hat{f}_{y_{t+h}|x_t}(y|x_t)$, and hence $\hat{F}_{y_{t+h}}^{-1}(0.5|x_t)$ is the conditional median.

For a chosen target probability π , the shortfall and longrise are defined, respectively, as

$$SF_{t+h} = \frac{1}{\pi} \int_0^\pi \hat{F}_{y_{t+h}}^{-1}(\tau|x_t) d\tau \quad LR_{t+h} = \frac{1}{\pi} \int_{1-\pi}^1 \hat{F}_{y_{t+h}}^{-1}(\tau|x_t) d\tau$$

While shortfall and longrise summarise the lower/upper tail behaviour of the conditional distribution in absolute terms. Conversely, downside and upside entropy measure the tail behaviour of the conditional distribution in excess of the tail behaviour exhibited by the unconditional distribution.

It is important to observe that this framework allows to capture the evolution of the predictive conditional distribution of output growth over time, and hence can capture different types of GDP vulnerability – i.e. an increase in the likelihood of large and negative realisation in GDP growth. For example, an increase in the conditional probability of a large fall of GDP growth can be generated either by an increase in left skewness and/or kurtosis, but also by an increase in the conditional variance correlating to a decline in the conditional mean. The latter, is the mechanisms found by [Adrian et al. \(2019b\)](#) when conditioning on the aggregate NFCI. In the next section, we will review the evidence provided in that work and show that, instead, a model conditioning on the nonfinancial leverage component of the NFCI, reveals the first type of risk.

3 Short-term Predictors of Growth at Risk

In this Section, we consider the specific features of the relation between some key financial indicators and GDP, by evaluating results from quantile regression models conditioning on different financial and real indicators. First, we focus on the in-sample properties of the coefficients obtained from quantile regressions to assess whether they show significant deviations from linearity. Second, we consider the out-of-sample predictive distribution of GDP growth produced by different models and analyse the time-varying behaviour of its moments. Finally, we consider how different measures of risk to growth move over the sample and in particular around recessions, to assess whether the models provide advanced warning of ‘vulnerabilities’ in GDP growth.

Specifically, we employ three models in which the dependent variable is always annualised, average GDP growth one- and four-quarters ahead, while the conditioning variables are respectively:

- (*model 1*) GDP growth at time t and the NFCI at time t ;
- (*model 2*) GDP growth at time t and nonfinancial leverage at time t ;
- (*model 3*) the real activity index, and the residual from a contemporaneous regression of the NFCI on the real activity index.

The first model corresponds to the model proposed in [Adrian et al. \(2019b\)](#), who focused on the NFCI as the key financial stress indicator. We will reproduce results in [Adrian et al. \(2019b\)](#), and adopt them as a benchmark for our discussion. The second model incorporates the nonfinancial leverage subcomponent of the NFCI as main indicator. The rationale for this choice is that this subcomponent appears to have a different informational content from the other subcomponents. In fact, as we have seen in [Section 1](#), the nonfinancial leverage subcomponent of the NFCI has smoother dynamics than the other subcomponents, reflecting the slow accumulation of debt from households and business and the subsequent phases of deleveraging. Moreover, this

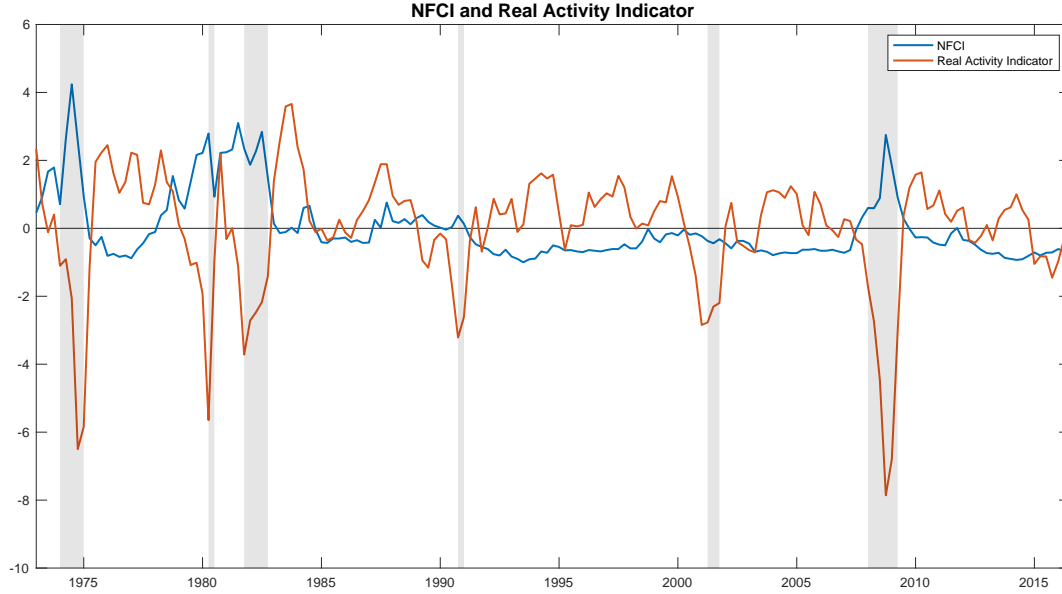


Figure 5: The real activity indicator (authors’ computation) and Chicago Fed’s NFCI, for the period from 1973q1 to 2015q1.

variable has been the focus of macro-prudential policies as it is similar (although not identical) to the credit gap monitored by the Basel Committee. Hence it is possible that this indicator may capture different aspects of growth at risk. Nonetheless, while we focus on this subcomponent we also provide results from models incorporating the others NFCI subcomponents.

The third model incorporates a real activity indicator together with the component of the NFCI that is orthogonal to our index of real economic activity. The real activity indicator is computed as the common factor of a set of real macroeconomic variables.⁵

The objective here is to ‘clean’ the NFCI from correlations with real variables to capture the additional informational content delivered by financial variables. In fact, as suggested by Figure 5, which plots the NFCI and the real factor, the two variables are negatively correlated (the overall correlation is -.5) especially in recessions and dominated by the large spike in the fourth quarter of 2008. The aim is to assesses the marginal impact of the NFCI in the conditional distribution of GDP growth over and beyond the information that is present in the real variables.

3.1 In-sample Quantile Regression Results

Results for *model 1* reproduce the findings in Adrian et al. (2019b): the estimated quantile coefficients of the NFCI regressor differ significantly across quantiles while those of GDP are flat over quantiles and not significantly different from what obtained by an OLS regression.⁶ The NFCI is almost always negatively associated with GDP growth indicating that, on average, an

⁵In both cases, the factors are estimated by maximum likelihood following Doz et al. (2012). The monthly real activity index was constructed from a mixed-frequency dataset featuring monthly and quarterly data and averaged across quarters.

⁶Following Adrian et al. (2019b), confidence bounds are computed, under the hypothesis of constant slopes, using the distribution of coefficients estimated in 1000 bootstrapped samples generated using a vector autoregression (VAR) with Gaussian errors, 4 lags and constant fitted to the full-sample evolution

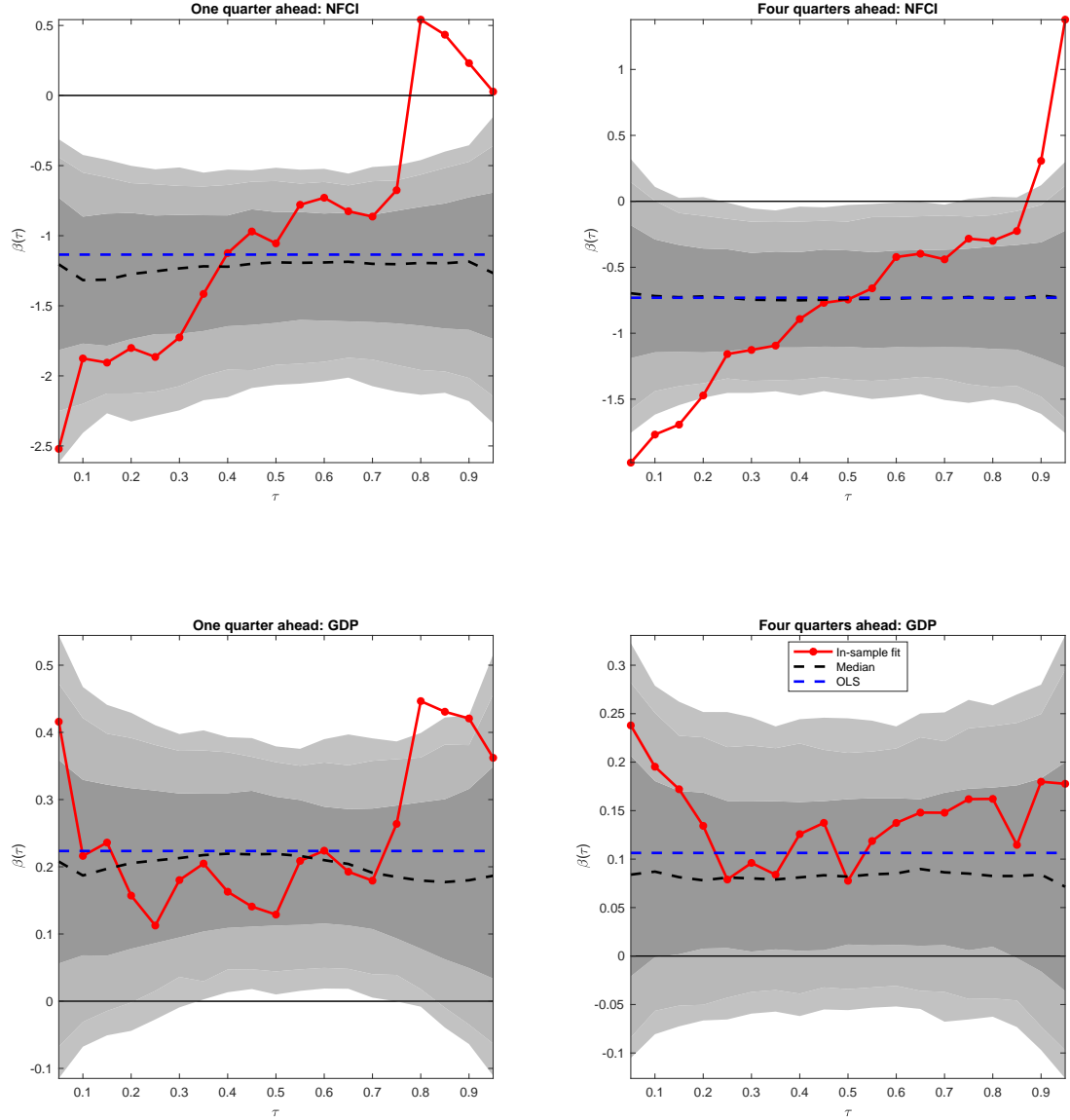


Figure 6: Quantile coefficients - *model 1*

increase in the index forecasts a reduction of GDP growth. Notably, and this is the key result in [Adrian et al. \(2019b\)](#), the estimates reveal a larger negative impact of a deterioration of financial conditions at the lower tail of GDP growth and a small negative or positive effect at the higher quantiles. The upward slope of the coefficients across quantiles and their negative values indicate that the relationship between financial conditions and GDP is non-linear. The implication of this result is that, as financial conditions deteriorate, the variance of the predictive distribution increases.

In contrast, results for *model 2*, suggest that the non-linear relationship between future growth and nonfinancial leverage is muted and below the significance level. Interestingly, the shape of the predictive variable and real GDP growth. Quantile coefficients estimates outside the bound indicate that the relation between GDP growth and the predictive variable is non-linear.

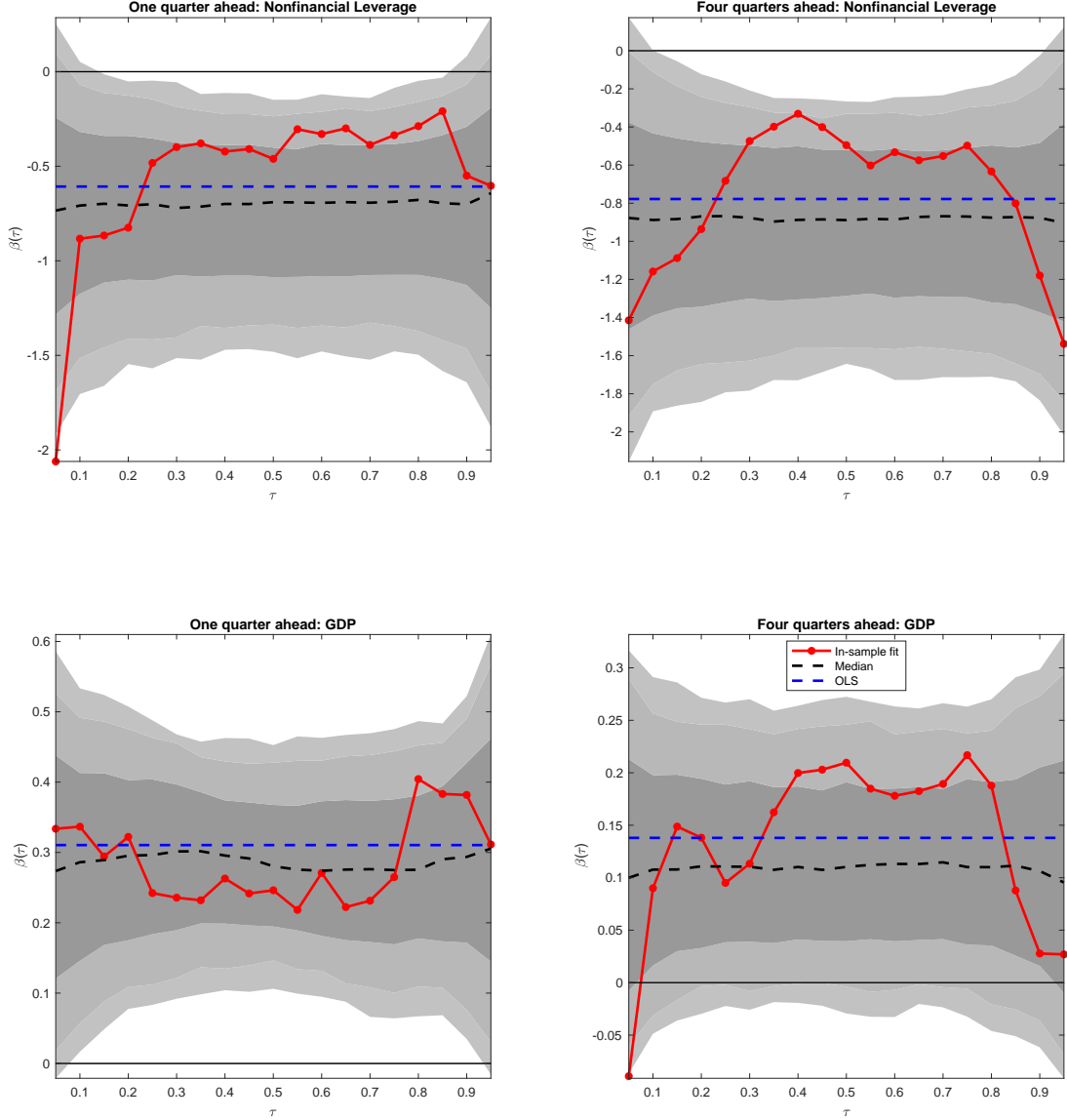


Figure 7: Quantile coefficients - *model 2*

the relationship is not upward sloping, potentially indicating larger negative effects of a marginal increase in nonfinancial leverage on both low and high quantiles of the GDP growth distribution.

Finally, *model 3* reveals that, at $h = 1$, both the real activity index and the orthogonal component of the NFCI have relatively large slopes in absolute values at the lower quantiles. However, for $h = 1$, movements across quantiles are more muted than for $h = 4$ and then for *model 1*. The real activity indicator seems to have a steeper slope than the ‘cleaned’ NFCI at $h = 4$, showing that the strong relationship in the left tail is not specific to financial conditions. However, the coefficients for the residual of the NFCI, in the lower tail, are inside or at the margin of the confidence bound for the null hypothesis of a linear relationship. Conversely, both predictors have coefficients for the higher quantiles outside the bands, where the effect of financial conditions is positive and larger than at the median.

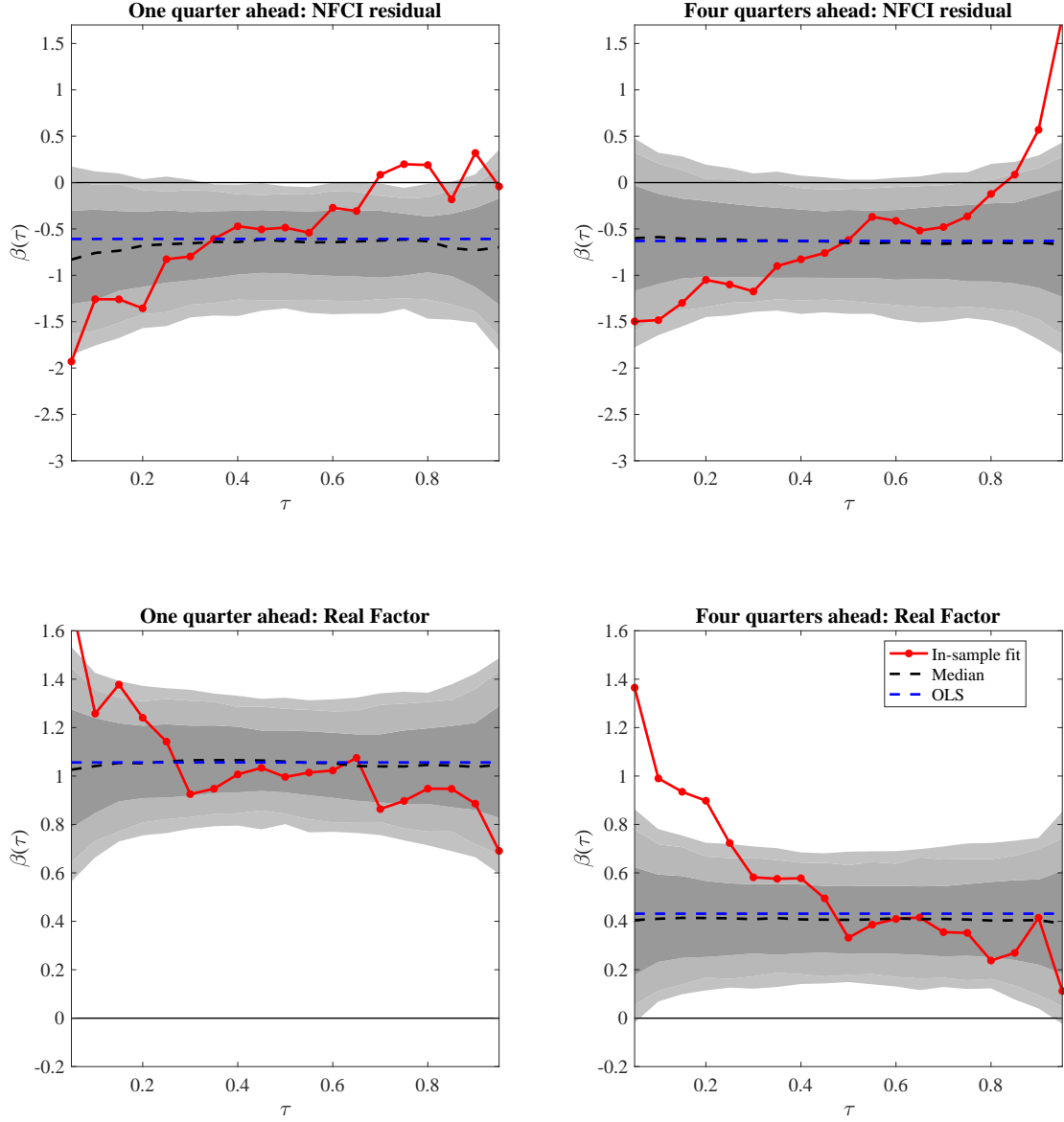


Figure 8: Quantile coefficients - *model 3*

Overall, these results point to a difference between the nonfinancial leverage subindex and the NFCI headline index for what concerns their effects on the predictive conditional distribution of the GDP growth. Importantly, although there is some evidence of a non-linear relationship between each of the two financial indicators and GDP growth, the statistical difference from that implied by a linear model, is not fully robust to the change of specification. The important question – to which we turn in the next Section – is whether the features emerged from the estimates of quantile regressions can help anticipating variations in the moments of the conditional distribution of GDP growth, and can therefore be exploited for ex-ante monitoring GDP vulnerabilities.

3.2 Out-of-sample Results

We now focus on the out-of-sample performance of *model 1* and *model 2*. We also show, for comparison, the results based on models incorporating other subcomponents of the NFCI. We first estimate the models following the two step methodology illustrated in the previous section and using data from 1973q1 to 1992q4. We then iteratively estimate the predictive distributions one- and four-quarters ahead, expanding the estimation sample, one quarter at a time, until the end of the sample in 2015q4.

We will ask the following questions: how do the moments of the predictive distributions vary over time? Can we predict an increase in GDP growth vulnerability? To this end, we report different key statistics for horizons $h = 1$ and $h = 4$: the time evolution of the four moments of the distribution, the expected shortfall for both horizons, the downside entropy of the unconditional distribution relative to the empirical conditional distribution and the predictive score. We do this for a number of different models.

3.2.1 NFCI as Predictor

Figures 9-11 show results comparing the model with GDP and a constant to the model with the NFCI as an additional predictor. Let us first comment on figures 9 and 10, which show the time evolution of the four moments of the fitted distributions over the out-of-sample period, for $h = 1$ and $h = 4$. The distributions of both models show a sharp decrease in the mean around the period of the great recession but, for the distribution conditional on the NFCI, we can also see a sharp increase in the variance. This out-of-sample results is in line with what we have seen for the in-sample quantile regressions coefficients for *model 1*: at lower quantiles the NFCI is associated with a decline in the mean and an increase in the variance of the conditional distribution. However, importantly, the spike in the variance lags the 2008 recession by a few quarters, since it results from the incorporation into the model, with a quarter of delay, of the spike in spreads in the fourth quarter of 2008. Skewness and kurtosis, on the other hand, are rather stable over the sample for both distributions and do not show any interpretable movement around recessions.

Let us now turn to the problem of predictability of risk vulnerability. Following [Adrian et al. \(2019b\)](#), we consider both left entropy and the expected shortfall. Left entropy measures the extra probability mass that the predictive density, conditional to the predictors, assigns to a left tail event, as compared to the probability assigned under the unconditional density. This is reported in Figure 11b which also plots the right entropy for comparison. The expected shortfall, reported in Figure 11c, summarises the left tail behaviour of the conditional distribution. If both conditional and unconditional distributions are negatively skewed, left (downside) entropy will be low and expected shortfall will be high. Both measures show that the model picks up the increase probability of a large loss in GDP growth with a lag. The estimated expected 5% shortfall one-quarter ahead, decreases dramatically in 2009q1, after the fall of Lehman Brothers in September 2008. The same is true for entropy. Results at four-quarters ahead, not surprisingly, are even more lagging. These results can be interpreted by looking at the predictive score (Figure 11a)

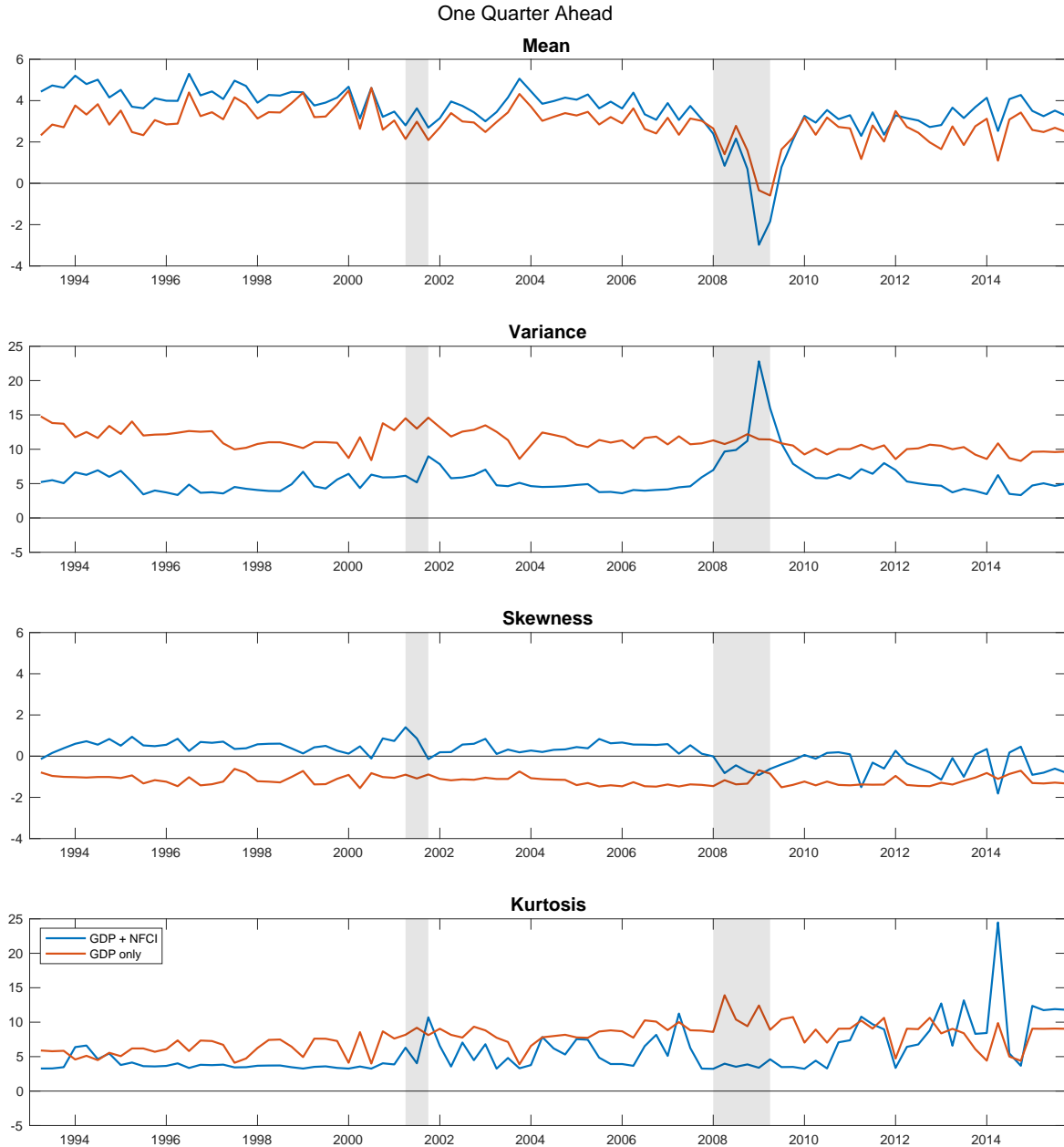


Figure 9: Time evolution of the four moments of the one-quarter ahead predictive distribution of GDP growth, from 1993q1 to 2015q4.

which shows that the model conditional on the NFCI improves the forecast outside recession, but does equally badly than the model conditional on lagged GDP only in recessions.

To provide some intuition, Figure 12 reports, for $h = 1$ (results for $h = 4$ are qualitatively similar) the two predictive distributions at different points in time, before and during the Great Recession (2007q4-2009q1). It does so for three different models where predictors are: NFCI residual from the regression on the real factor and GDP, the real factor and GDP and GDP only. It show that as financial stress spikes up in the fourth quarter of 2008, the conditional forecast of both the model including the NFCI residual and that including the real factor becomes broader,

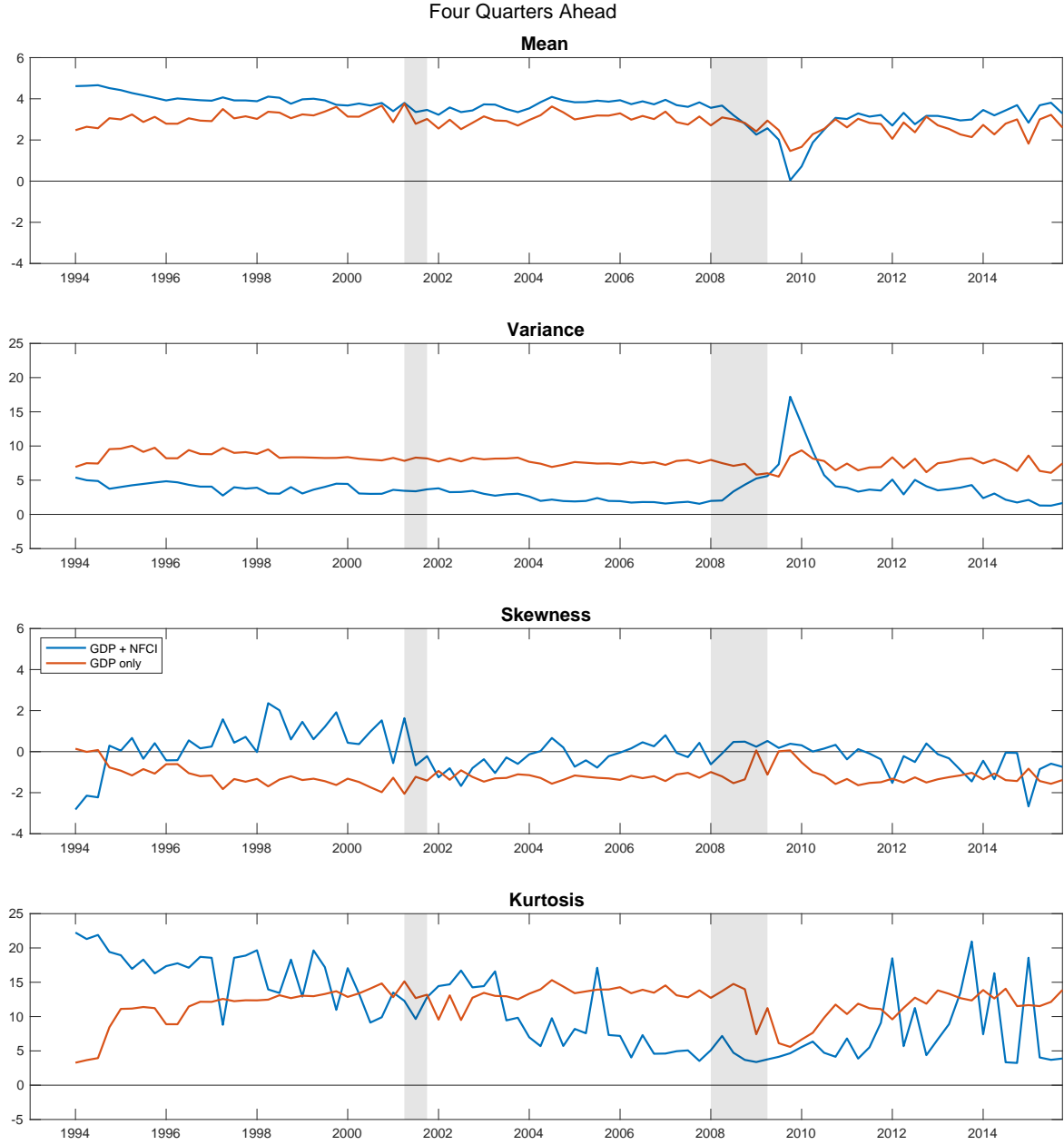


Figure 10: Time evolution of the four moments of the four-quarter ahead predictive distribution of GDP growth, from 1993q1 to 2015q4.

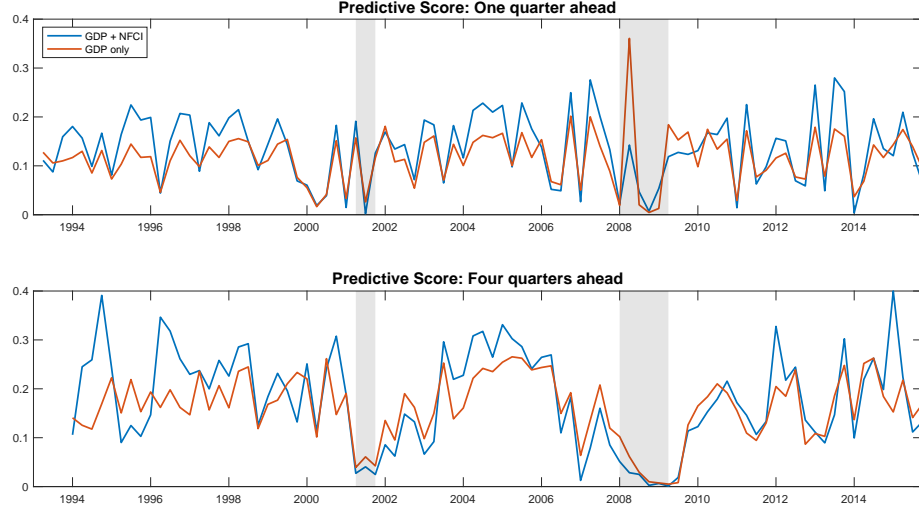
giving higher likelihood to a wider range of events. However, this movement is particularly strong for the former model suggesting that both the NFCI and the real factor have stronger correlations with GDP growth in the tails. Indeed, we observe both a negative large change in the conditional mean and a positive large change in the conditional variance. Since the performances of both models, as measured by the predictive score deteriorate, this can be seen as an indication of high uncertainty in the prediction.

3.2.2 Non-financial Leverage and Other Subcomponents of the NFCI

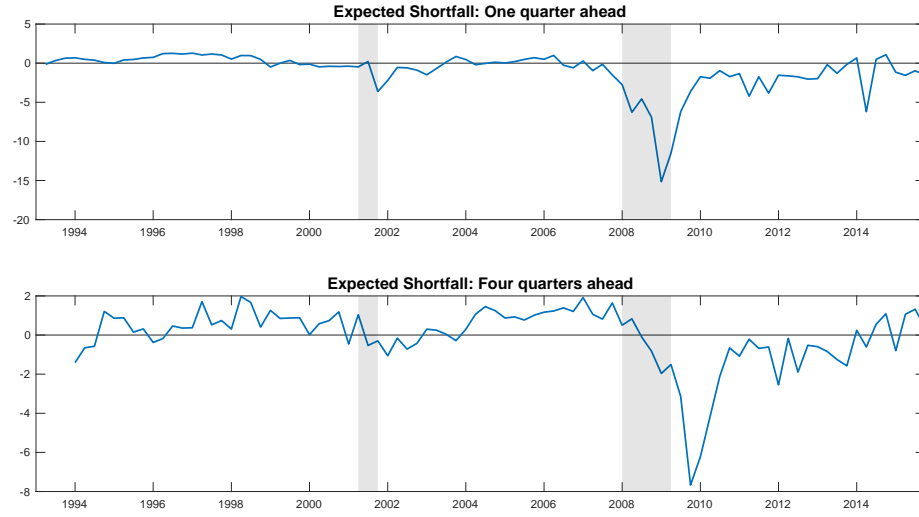
In Figures 13 and 14, we report the time series evolution of the moments of the one-step and four-step ahead distributions, respectively, of *model 2* and also of three alternative models conditioning on the three other subcomponents of the NFCI – i.e. credit, risk and financial leverage. As it could have been guessed from the dynamics of the four components illustrated in Section 1, the conditional distribution including nonfinancial leverage has distinct characteristics which are explained by the smooth cyclical behaviour with peaks possibly leading recessions (see Figure 2). In fact, unlike the other sub-indices, nonfinancial leverage seems to provide a leading signal for the 2008 recessions in terms of mean, variance and negative skewness of the predictive densities at both horizons.

The predictive score, reported in Figure 15, shows that, at $h = 1$, *model 3* has performances in line with that of the model with lagged GDP only, for most of the sample. For $h = 4$, however, the model does very well between 2007q4 and 2008q4 and poorly otherwise. It seems that this variable provides leading information to forecast the last recession but not otherwise. This is confirmed by the estimate of the expected shortfall in Figure 16.

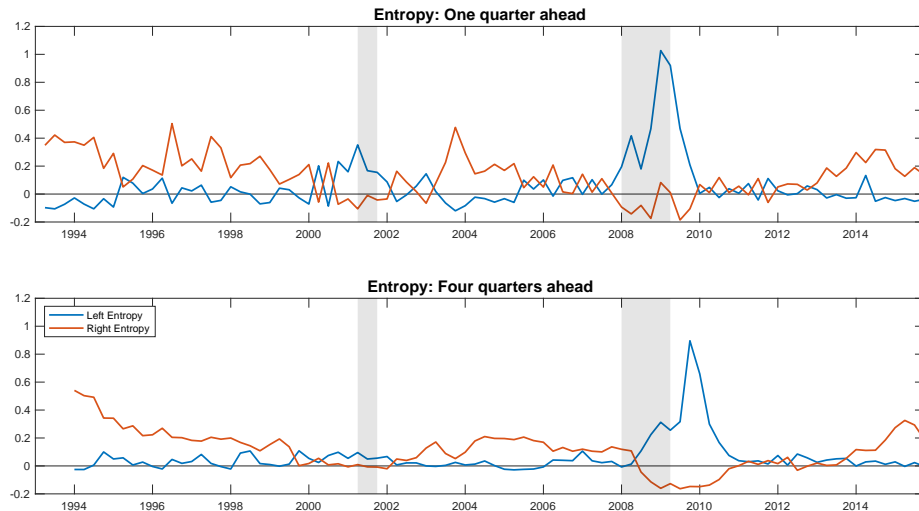
We further explore these results by plotting in Figure 17 and Figure 18 the quarter by quarter evolution of the predictive distributions in the period of the Great Recession, from 2007q4 to 2009q1. The charts confirm that, at $h = 4$, the model captures a shift of the distribution to the left and an increase in left skewness and kurtosis. Indeed, this model shows some predictive power with respect to GDP vulnerability, this time driven by skewness and kurtosis rather than variance in relation to the last recession. However, as we have seen, this result seems to be specific to this particular episode.



(a) Predictive Score



(b) Expected Shortfall



(c) Entropy

Figure 11: Time evolution of the predictive score (a), expected shortfall (b), and entropy (c) of the one- and four-quarter ahead predictive distribution of GDP growth, from 1993q1 to 2015q4.

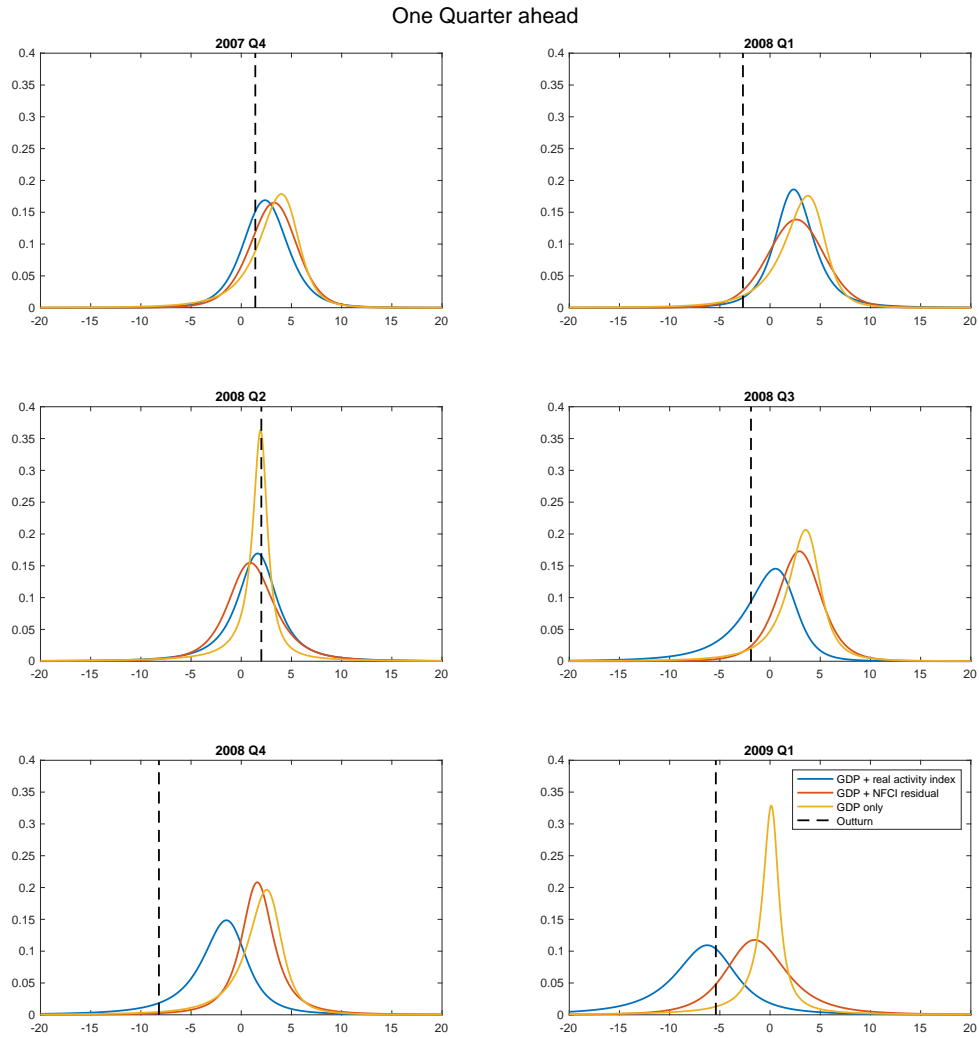


Figure 12: One-quarter ahead, quarter by quarter evolution of the predictive distributions in the period of the Great Recession, from 2007q4 to 2009q1 - different models

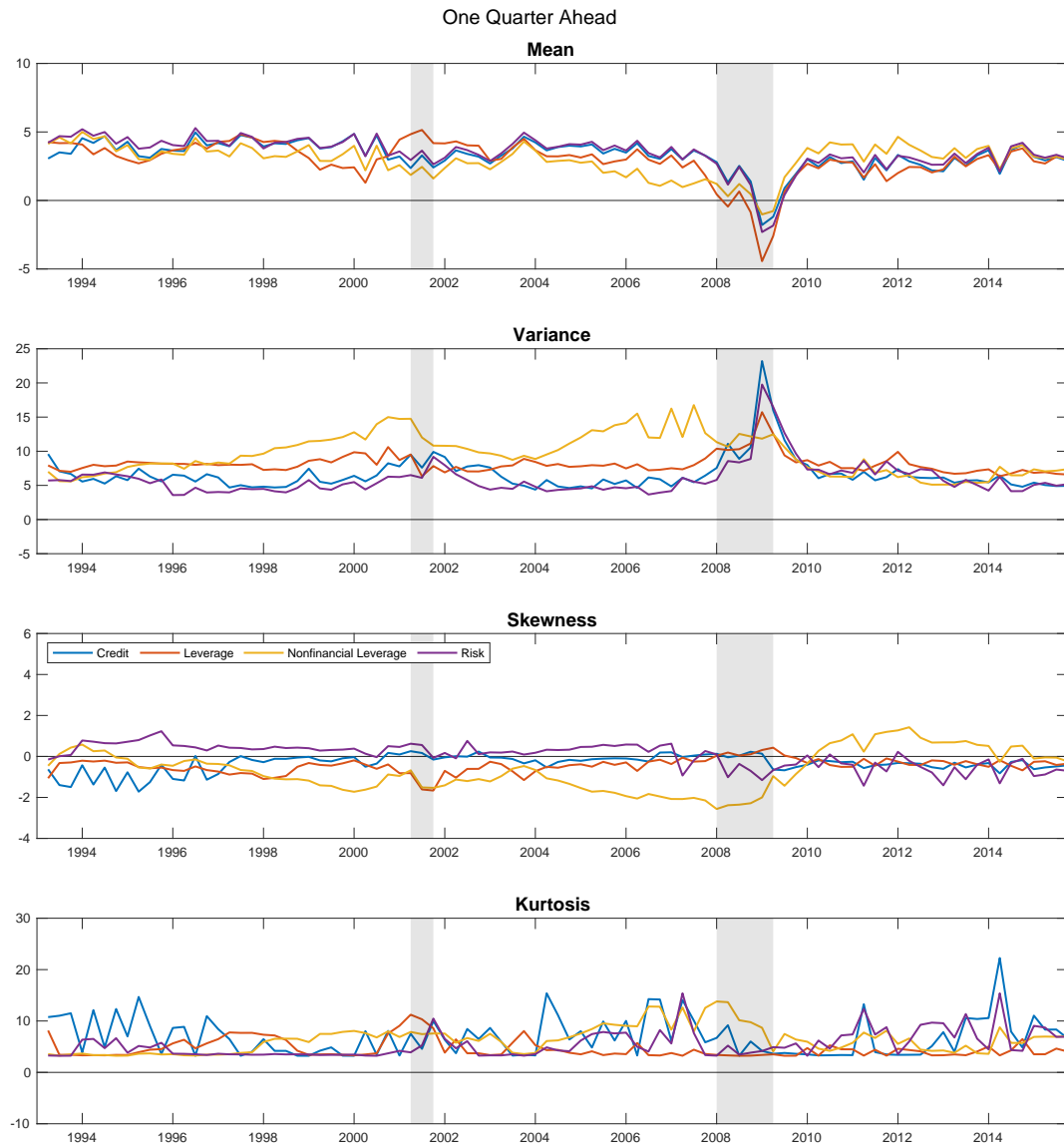


Figure 13: Time evolution of the four moments of the one-quarter ahead predictive distribution of GDP growth of quantile regressions with NFCI subindices, from 1993q1 to 2015q4.

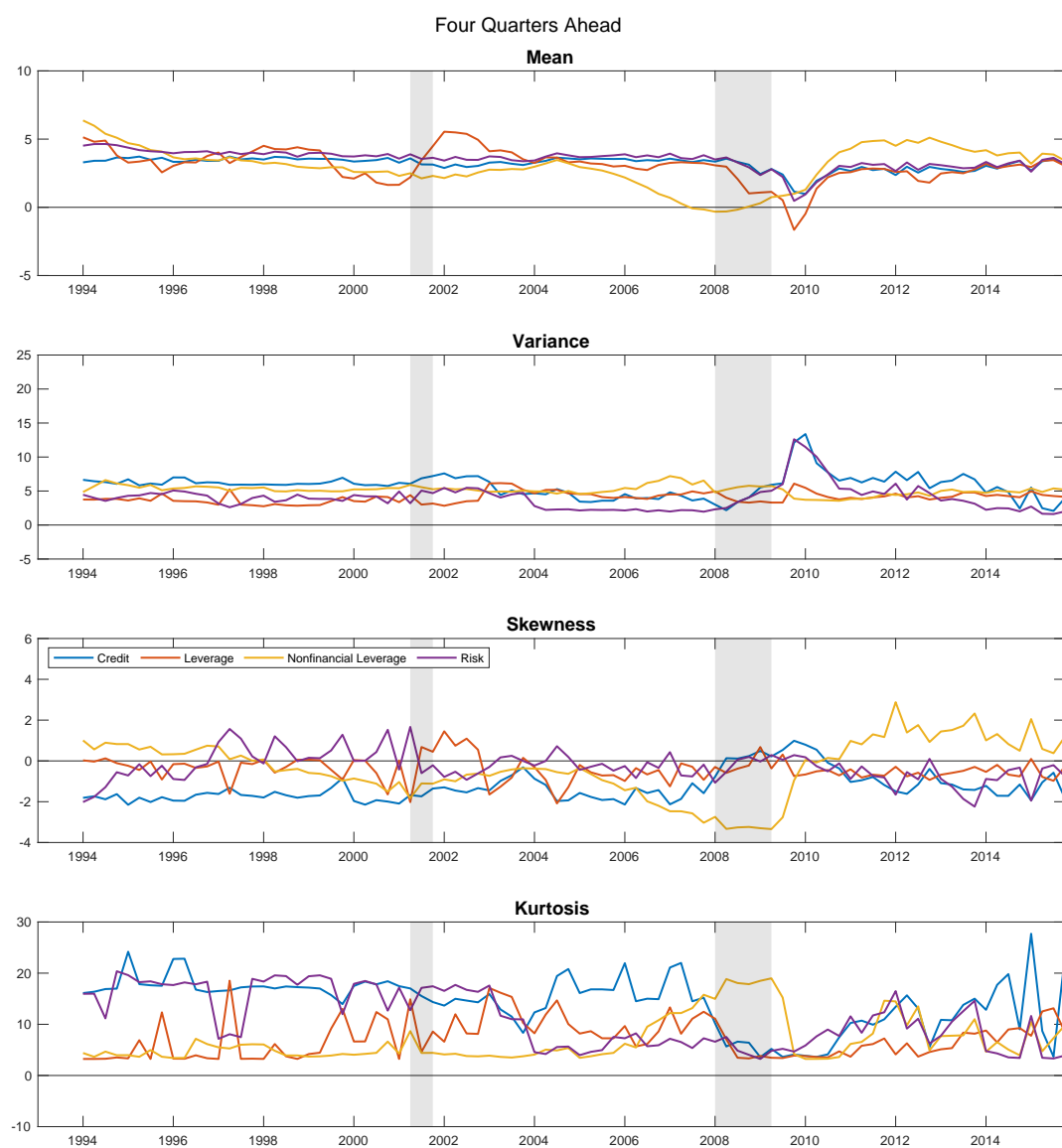


Figure 14: Time evolution of the four moments of the four-quarter ahead predictive distribution of GDP growth of quantile regressions with NFCI subindices, from 1993q1 to 2015q4.

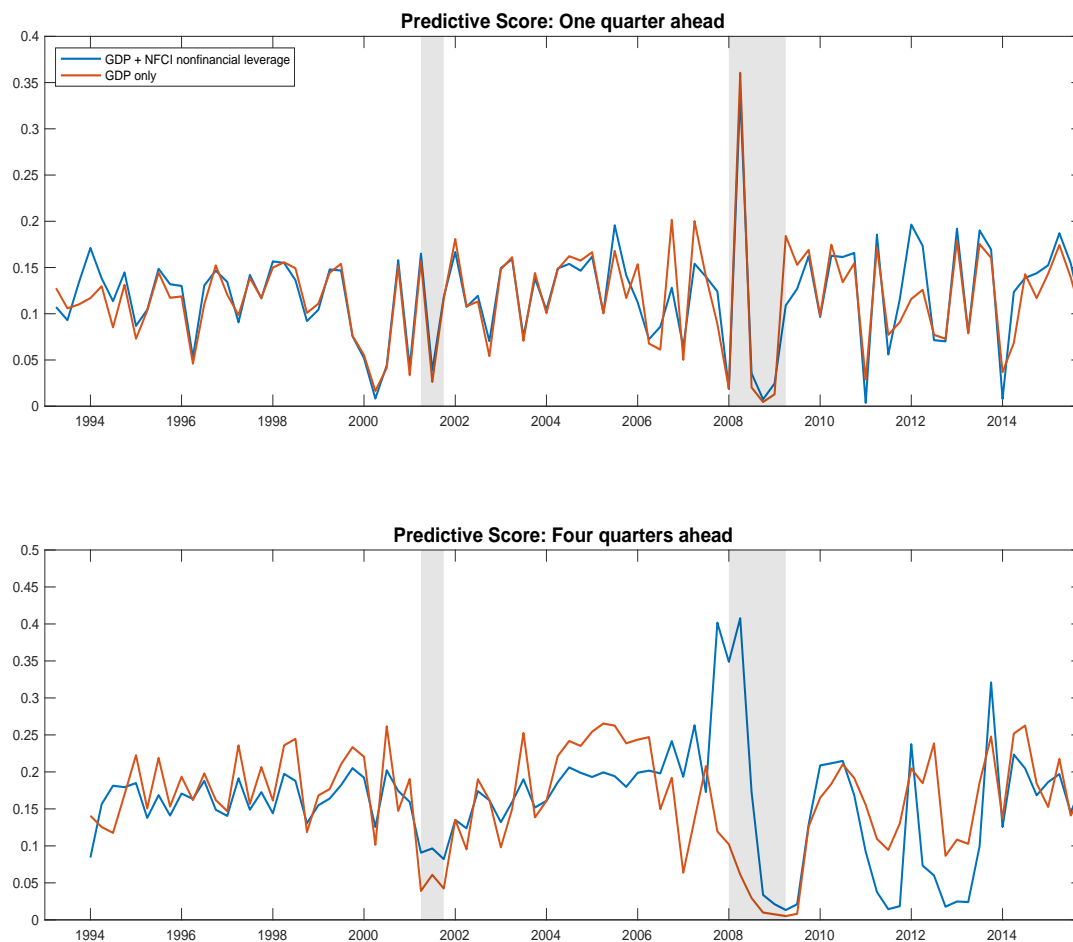


Figure 15: Predictive Score of the quantile regression with NFCI nonfinancial leverage for $h=1$ and $h=4$.

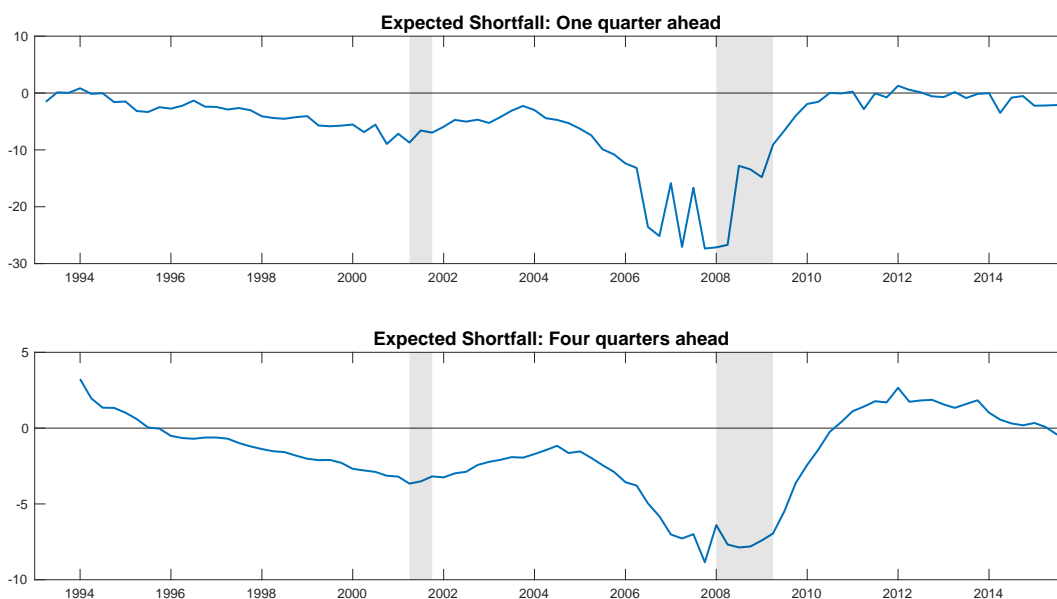


Figure 16: Time evolution of the shortfall for the one and four-quarter ahead predictive distribution of GDP growth of quantile regressions with the NFCI nonfinancial leverage subindex, from 1993q1 to 2015q4.

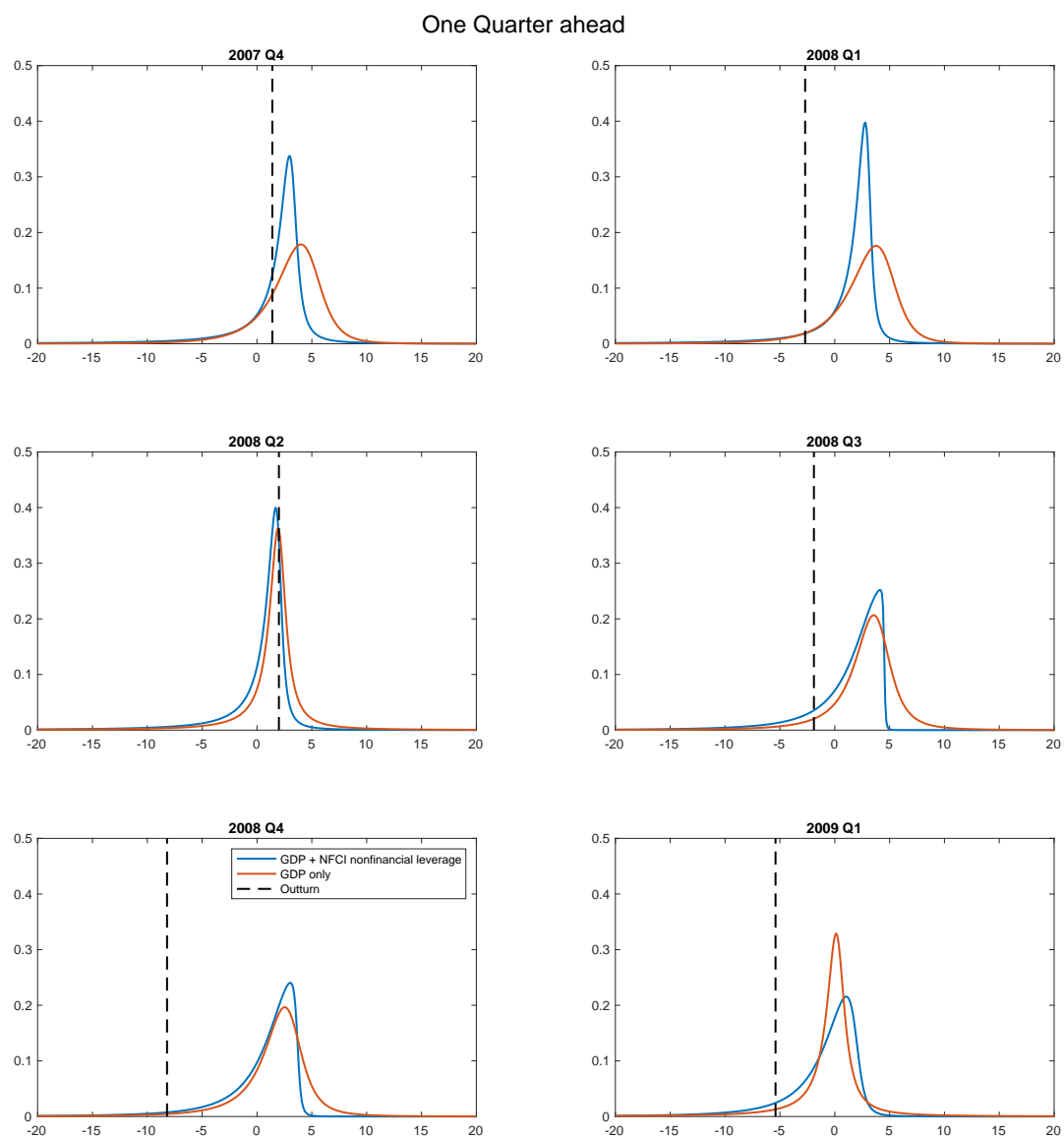


Figure 17: One-quarter ahead, quarter by quarter evolution of the predictive distributions in the period of the Great Recession, from 2007q4 to 2009q1.

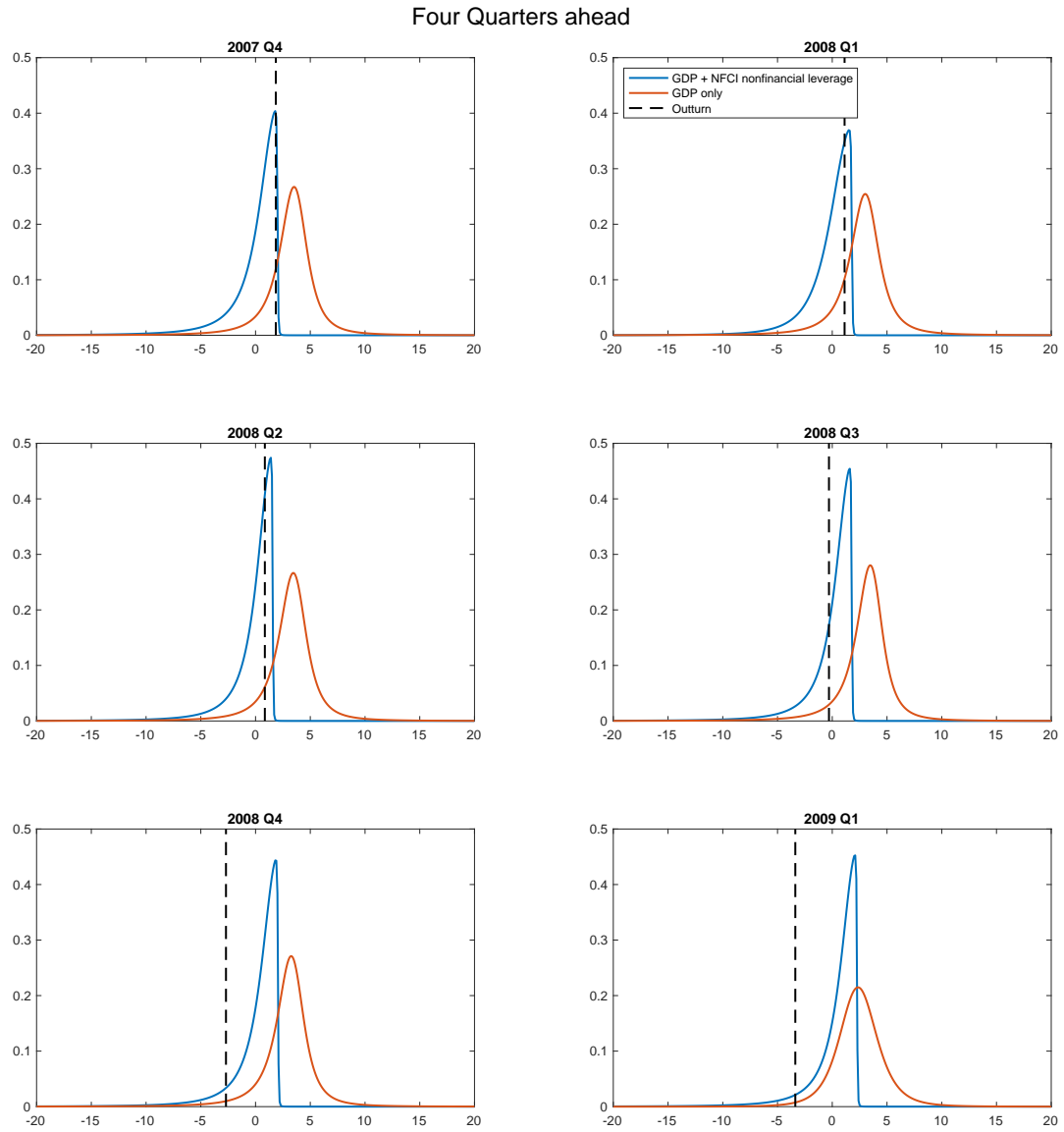


Figure 18: Four-quarters ahead, quarter by quarter evolution of the predictive distributions in the period of the Great Recession, from 2007q4 to 2009q1

4 Nowcasting with Real and Financial Factors

In this section, we assess the predictive ability of the quantile regression model in real time, focusing on the nowcast of current quarter ($h = 0$). Although this is a very short-term horizon for the design of macro-prudential policies, it is a relevant one for prediction since the literature has shown that, generally, there is very little predictability for the mean of GDP growth beyond one quarter (see, for example, [Giannone et al., 2008](#)). Also, our results from previous sections, seem to indicate that the model has limited predictive ability on longer horizon.

We report results from two models: the benchmark model, in which the conditioning variables are a constant, the NFCI and GDP and an alternative model including a constant, GDP and the real activity index described earlier.⁷ Although the real index is quarterly, we have constructed it out of a mixed frequency model including monthly variables by averaging the monthly indices for each quarter. This is indeed how it is used for nowcasting GDP (see [Giannone et al., 2008](#)). For both the GDP and the real index we will consider their real time vintages. Not so for the NFCI which will be considered in its revised version due to lack of real time data availability. As in the tradition of the now-casting literature, we will update the now-cast in relation to the calendar of data releases.

We begin the out-of-sample forecasting exercise in 1993Q1. For each quarter, we position ourselves on the last day of the quarter, estimate the real index using the most up-to-date data vintage, and produce direct density forecasts for GDP growth for the current quarter. In each quarter we estimate the real factor and the quantile regression parameters using an expanding dataset starting in 1973Q1.

Table 1 shows, for each of the macroeconomic variables used to construct the factor, the transformation prior to estimation and the average publication lag. The column labeled ‘First Vintage’ shows the first date on which real-time vintages are available for the corresponding variable. Variables that do not have real-time vintages available at the beginning of the forecasting exercise are added to the factor estimation once the first vintage becomes available. The column labeled ‘Publication Lag (days)’ shows the number of days from the first day of the reference period to the release date of the variables.

Importantly, in the US, the first estimate of GDP is usually released around 120 days after the beginning of the quarter to which the release refers to. This places the release date of y_t towards the end of the first month of quarter $t + 1$. Thus, on the last day of quarter t , we have an estimate of the NFCI and the real index for the current quarter, but we do not yet have y_t , the first estimate of current quarter GDP. Thus, we produce a forecast for $h = 0$, which refers to the quarter t , and can be thought of as a ‘density nowcast’. Further the vector of conditioning variables, x_t , includes the financial and real indices for quarter t and GDP growth for quarter $t - 1$. This is different from the out-of-sample exercise in [Adrian et al. \(2019b\)](#) and our exercise in the previous section since there x_t contains the NFCI and GDP growth for quarter t . Given the publication lag of GDP, the forecasts of the conditional distribution can realistically only be

⁷The real activity index adopted in this section and in the previous one differ due to limits in the availability of some variables, in real-time.

Table 1: ‘First vintage’ is the date of the first real-time vintage available on the Alfred database. The mean publication lag is the average number of days between the data release and the first day of the period that the data release refers to.

	Series	Transform	First Vintage	Pub. Lag (days)
1	Industrial Production	MoM%	1/26/1927	48
2	Capacity Utilization	MoM	11/15/1996	45
3	Real Disposable Per Inc	MoM%	12/18/1979	64
4	Real PCE	MoM%	11/19/1979	64
5	Employees: Nonf Payrolls	MoM	5/6/1955	35
6	Employees: Priv. Ind	MoM	9/3/1971	34
7	Retail Sales	MoM%	6/13/2001	43
8	Housing Starts	MoM	7/21/1960	47
9	New Pvt Housing Un Author	MoM	8/17/1999	48
10	Total Business Inventories	MoM%	11/15/1996	74
11	New Orders: Durable goods	MoM%	8/4/1999	55
12	Exports	MoM%	1/17/1997	72
13	Imports	MoM%	1/17/1997	72
14	UOM: Consumer Sentiment	MoM	7/31/1998	27
15	Real Gross Domestic Product	QoQ%	12/4/1991	120

produced around 30 days after the end of quarter t , at which time the NFCI and the real index for time t no longer contain the most recent available information, since they are estimated with data series that are released at higher frequency. We overcome this problem by conditioning on the information set as of the last day of each quarter. The design of the real time out-of-sample exercise is summarised by the diagram below.

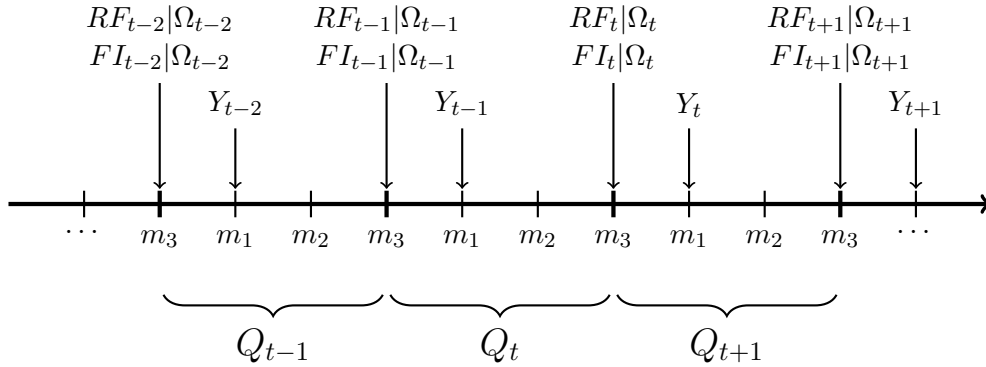


Figure 19: The information flow in the real time exercise. Y_j indicates the release dates of GDP for quarter Q_j and m_i are the months for $i = 1, 2, 3$ in each quarter Q_j . RF_j and FI_j are the real factor and financial index of quarter Q_j conditional on the information set Ω_j , which contains the data vintage available on the last day of quarter Q_j . In the real time nowcasting exercise, we construct density forecasts of Y_j conditional on $RF_j|\Omega_j$, $FI_j|\Omega_j$, and Y_{j-1} ,

Figures 20 reports the evolution over time of the four moments of the predictive distributions when conditioning on the real factor and when on the NFCI for $h = 0$. The top panel shows that the model with the real factor tracks the mean of the distribution better during the crisis,

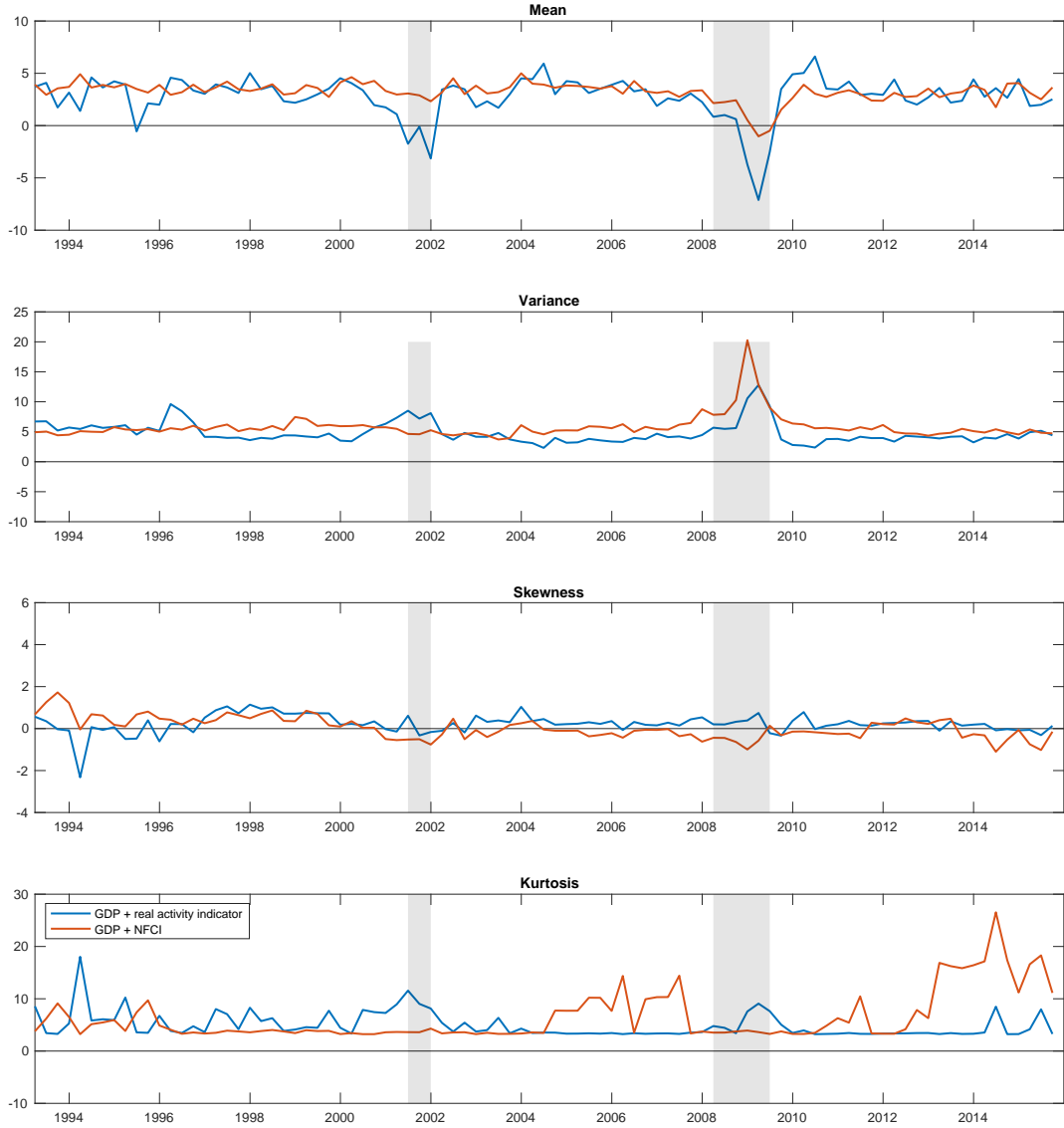


Figure 20: Time evolution of the four moments of nowcast predictive distribution of GDP growth at $h = 0$ of quantile regressions with NFCI and the real factor, from 1993q1 to 2015q4.

by nowcasting a contraction of output. Differently, the model with the NFCI does not seem to correctly capture this feature. Both models show a spike of variance during the 2008 recession, but only the real factor captures it in the 2001 recession. Neither models show much action in the third moment.

Figure 21 plots the evolution of the expected shortfall for the two models. The analysis points to the fact that conditioning on a real factor or conditioning on the NFCI we obtain similarly weak and not timely signals of risk of GDP vulnerability, in real time. The spikes around recessions in the two indicators are contemporaneously correlated and seem to contain relatively little advanced information. In other words, the two factors seem to incorporate highly correlated information. We interpret this as an indication that while financial indicators are able

to aggregate a lot of information in real time, they do not contain much advanced information over and above what is available in real-time data.

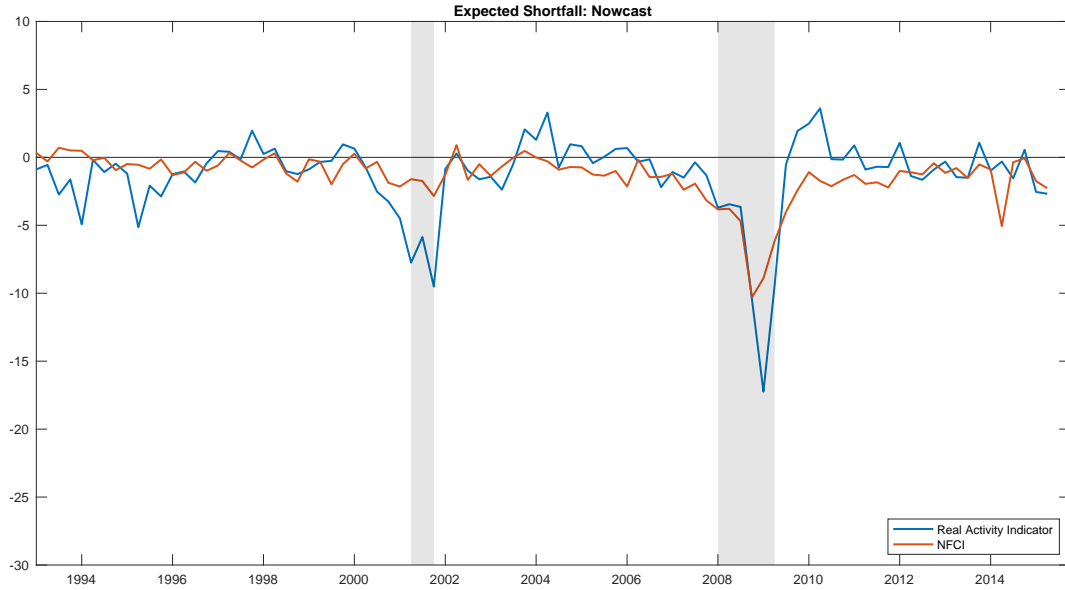
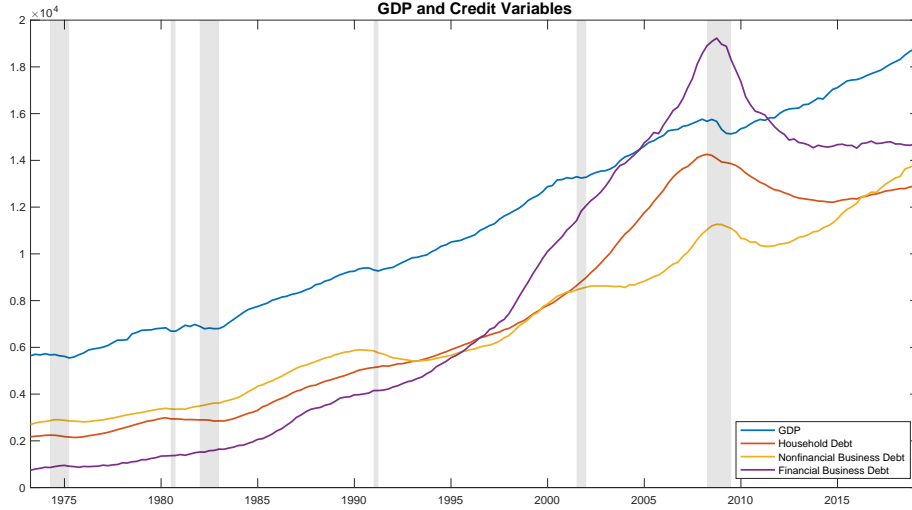


Figure 21: Time evolution of the expected shortfall of the real time model for the current quarter predictive distribution of GDP growth, from 1993q1 to 2015q4.

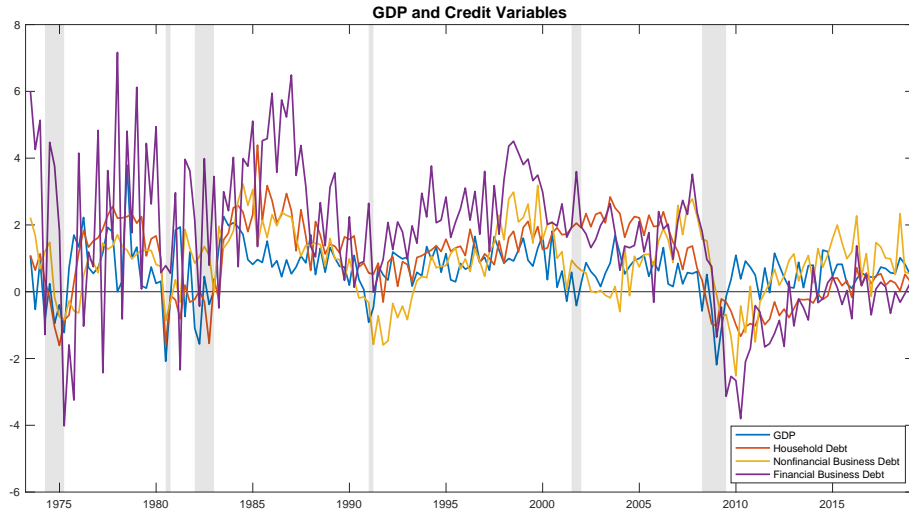
5 A Semi-Structural Macro-Finance Model

As seen in Section 1, financial leverage exhibits a medium-run behaviour characterised by periods of slow increase followed by periods of normalisation. Motivated by this observation, in this Section, we analyse the joint properties of real economic activity and credit variables, through the lens of a semi-structural trend-cycle model (see [Harvey, 1985](#) and [Hasenzagl et al., 2018](#)). To further motivate this approach, Figure 22 plots GDP, households', nonfinancial and financial business' leverage in levels. The plots show that output and debts grow upwards for much of the sample, at a similar rate, albeit the debts variables exhibit persistent periods of higher growth followed by periods of adjustment. In other words, periods in which debt grows protractedly at higher speed than output are followed by deleveraging to bring debt back to a sustainable level (see, for example, discussions in [Jorda et al., 2011](#), [Schularick and Taylor, 2012](#), [Jorda et al., 2013](#)). Indeed, debt sustainability requires that the debt-to-GDP ratio is constant in the long-run (up to shifts due to technological innovation). However, it can fluctuate in the medium-run with the business cycle. Due to the pro-cyclicality of credit, we expect leverage to move counter-cyclically with respect to the output gap, possibly with lagged dynamics. Also as observed, debt variables can deviate from long-run equilibrium and business cycle relations. These are potentially the episodes in which excess leverage and financial fragilities accumulate.

These considerations motivate a macroprudential approach to the monitoring of financial variables based on an indicator of excess leverage constructed as deviation from the long-run credit-to-GDP ratio. For example, the influential work done at the BIS (see [Borio and Lowe,](#)



(a) Levels



(b) Growth Rates

Figure 22: Time series in levels (a), and growth rates (b) of output, households' and business debt, from 1973q1 to 2019q1. All variables are in billions of 2012 US Dollars.

2002, Borio, 2014, Drehmann et al., 2012) has proposed the concept of ‘credit gap’, defined as the difference between the credit-to-GDP ratio and a long-term trend captured by a Hodrick and Prescott (HP) filter with a large smoothing parameter.⁸ This to capture the notion of a slow moving ‘financial cycle’, developing at slower frequency than the standard business cycle. Such defined notion of credit gap provides foundation to the recommendation of the [Basel Committee for Banking Supervision \(2010\)](#) to adopt, as main indicator, a measure of excess leverage constructed as the difference between the credit to GDP gap and its trend.

This approach has been criticised on the ground that HP filtering produces distorting results due to end-point issues, dependence on the initial values, smooth transition and high-pass behaviour (see, for a recent discussion on the issue, [Hamilton, 2018](#) and [Drehmann and Yetman,](#)

⁸[Borio and Lowe \(2002\)](#) suggest that, for the credit-to-GDP gap, λ be set equal to 400,0000.

2018). For example, [Repullo and Saurina \(2011\)](#) have shown that the credit-to-GDP gap is negatively correlated with GDP growth – this being a sign of the countercyclical behaviour of this variable at business cycle frequencies. As an alternative indicator of financial fragility, they advocate the use of credit growth since it is positively correlated with GDP growth.

Taking stock on this debate, we propose a novel methodology to extract a measure of excess leverage in credit variables, defined as deviations of the credit growth from the output trend-growth that are not due to business cycle fluctuations. Our objective is to provide a stylised example for how to construct a tool for medium-horizon monitoring of the building up of financial fragility in the economy. The model’s methodology builds on our recent research on inflation (see [Hasenzagl et al., 2018](#)) and it is similar in spirit, although not in the specification, to [Rünstler and Vlekke \(2018\)](#) and [Lang and Welz \(2018\)](#). Importantly, it does not rely on the adoption of a specific filter and employs variables in levels, as input.

5.1 A Trend-Cycle Model for Excess Leverage

The trend-cycle model provides a stylised description of real and credit variables by identifying the following components: (i) variable-specific non-stationary trends τ_t^j that can have both a common growth rate, and an idiosyncratic one; (ii) a common, stationary cycle ψ_t^{bc} which we interpret as the business cycle component; (iii) an independent, stationary cycle ψ_t^j that captures variable-specific but stationary dynamics, nonclassical measurement error and other sources of noise. This description is motivated by the observations that credit and real variables co-move along the business cycle, and should grow at the same rate in the long-run. However, episodes of larger or lower than equilibrium growth can materialise and these should be taken as indicators of risk accumulation.

We model real and credit variables as follows

$$y_t = \psi_t^{bc} + \tau_t^y + \psi_t^y \quad (5)$$

$$u_t = \delta(L)^u \psi_t^{bc} + \tau_t^u + \psi_t^u, \quad (6)$$

$$e_t = \delta(L)^e \psi_t^{bc} + \tau_t^e + \psi_t^e, \quad (7)$$

$$hd_t = \delta(L)^h \psi_t^{bc} + \tau_t^h + \psi_t^h, \quad (8)$$

$$bd_t = \delta(L)^b \psi_t^{bc} + \tau_t^b + \psi_t^b, \quad (9)$$

$$fd_t = \delta(L)^f \psi_t^{bc} + \tau_t^f + \psi_t^f. \quad (10)$$

where y_t is output, u_t and e_t unemployment and employment respectively, while hd_t , bd_t , and fd_t are households’, nonfinancial business’, and financial business’ debt.⁹ In the model, the

⁹All variables are standardised, by dividing each of them for the standard deviation of its first differences. This standardisation is helpful in extracting common components, and follows the same intuition that is applied to factor models. Empirically, over our sample period, the standard deviation of the first differences of household, nonfinancial business, and financial business debt relative to the standard deviation of the first difference of real GDP are 1.47, 1.35, and 2.76, respectively. This implies that a one unit increase in the trend growth of GDP is associated with a slightly larger than one to one increase in household and nonfinancial business debt trend growth and a nearly threefold increase of financial business debt trend growth.

Table 2: Data and transformations. The table lists the macroeconomic variables used in the trend-cycle model. Household debt is the sum of the variables ‘Household Debt in Home Mortgage’ and ‘Household Debt in Consumer Credit’, published by the Federal Reserve Board. Nonfinancial Business Debt is also published by the Federal Reserve Board. The debt variables have been deflated using the GDP deflator.

Variable	Symbol	Transformation
Real GDP	y_t	Log-Levels
Employment	e_t	Log-Levels
Unemployment Rate	u_t	Log-Levels
Household Debt	hd_t	Log-Levels
Nonfinancial Business Debt	bd_t	Log-Levels

output gap – defined as the stationary deviation of output from its potential – is the primitive of the business cycle. To allow for potential heterogenous dynamics between the business cycle and credit and labor market variables all variables except for y_t also include the first lag of the business cycle component – i.e. $\delta(L) = \delta_1^j + \delta_1^j L$, is a variable-specific lag polynomial of order one. Table 2 reports details of the variable incorporated in the baseline model. All of the variables enter the model in log-levels, since this allows interpreting the drifts as growth rates.¹⁰

The independent trends in y_t , hd_t , and bd_t , follow random walks with a common trend growth rate, captured by a stationary time-varying drift μ_t . We allow credit variables to move off the equilibrium relationship following idiosyncratic stationary but time-varying drifts μ_t^h and μ_t^b . It is worth stressing that these assumption capture both the idea that in the long-run credit-to-GDP should be constant, up to technology shifts that can move the trends (i.e. the shock to the unit-root trends, in our model), and the idea that there can be episodes in which credit variables grow persistently above or below trends to then normalise.

More formally, the trends are specified as follows:

$$\tau_t^y = \mu_{t-1} + \tau_{t-1}^y + u_t^y, \quad u_t^y \sim \mathcal{N}(0, \sigma_y^2), \quad (11)$$

$$\tau_t^h = \mu_{t-1} + \mu_{t-1}^h + \tau_{t-1}^h + u_t^h, \quad u_t^h \sim \mathcal{N}(0, \sigma_h^2), \quad (12)$$

$$\tau_t^b = \mu_{t-1} + \mu_{t-1}^b + \tau_{t-1}^b + u_t^b, \quad u_t^b \sim \mathcal{N}(0, \sigma_b^2). \quad (13)$$

where the time-varying drifts are modelled as persistent AR(1) processes.¹¹ For $j \in \{c, hd, bd\}$, we have

$$d_t^j = \rho d_{t-1}^j + v_t^j, \quad u_t^j \sim \mathcal{N}(0, s_j^2). \quad (14)$$

¹⁰We have considered the model both in levels and log levels. The results for the level version are available on request and they present the same features of results reported here.

¹¹For ease of estimation, in this version of the paper we fix ρ to 0.99. Results are not sensitive to setting the parameter to 0.9.

Conversely, the trend in the unemployment rate follows a driftless random walk and the trend in employment follows a random walk with constant drift:

$$\tau_t^u = \tau_{t-1}^u + u_t^u, \quad (15)$$

$$\tau_t^e = d + \tau_{t-1}^e + u_t^e, \quad (16)$$

providing a model-consistent measure of ‘equilibrium unemployment’ and ‘trend employment’, respectively. The common and idiosyncratic cycles are modelled as stochastic cycles, in the form of ARMA(2,1) processes with complex roots, and can be written in the following form:

$$\begin{pmatrix} \psi_t^j \\ \psi_t^{*j} \end{pmatrix} = \rho^j \begin{pmatrix} \cos(\lambda^j) & \sin(\lambda^j) \\ -\sin(\lambda^j) & \cos(\lambda^j) \end{pmatrix} \begin{pmatrix} \psi_{t-1}^j \\ \psi_{t-1}^{*j} \end{pmatrix} + \begin{pmatrix} v_t^j \\ v_t^{*j} \end{pmatrix}, \quad \begin{pmatrix} v_t^j \\ v_t^{*j} \end{pmatrix} \sim \mathcal{N}(0, \varsigma_j^2 I_2) \quad (17)$$

where $j \in \{bc, y, u, e, hd, bd\}$ and ψ^{*j} , is a term capturing an auxiliary cycle (see [Harvey, 1985](#)). For stationarity, we impose $0 < \lambda^j \leq \pi$ and $0 < \rho^j < 1$ for all cycles. As in [Hasenzagl et al. \(2018\)](#), we estimate the model using Bayesian methods (see also [Harvey et al., 2007](#)), and maximise the posterior with a Metropolis-Within-Gibbs algorithm.¹²

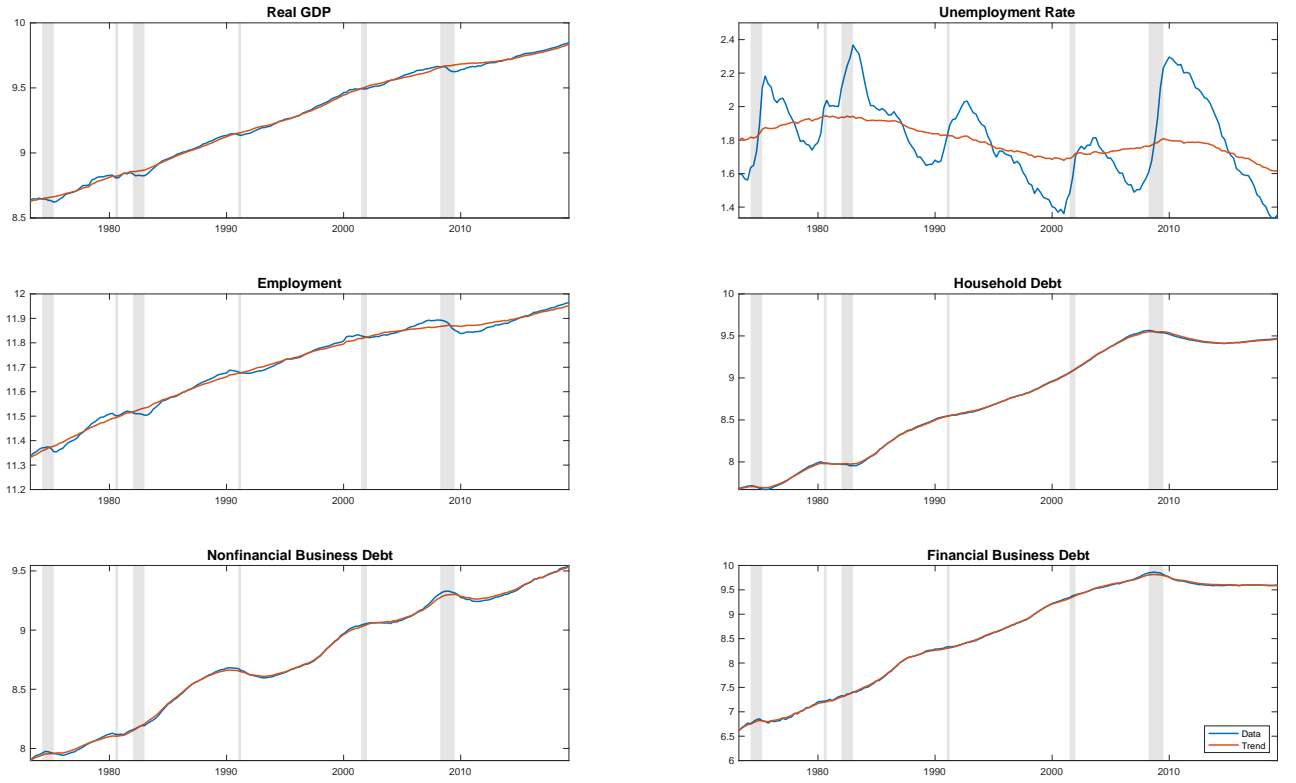
It is important to stress that this model specification can provide a useful indicator of the build-up of ‘excess leverage’ in the economy in the form of the idiosyncratic credit growth that signals, as we have described, persistent (although stationary) deviations from equilibrium growth of the economy. Also, the assumptions underpinning the model provide a clear interpretation of the various components and deliver a more transparent way of decomposing the data that is free from the distortions and limitations of the HP filter.

5.2 A Narrative of Financial Fragilities in the US

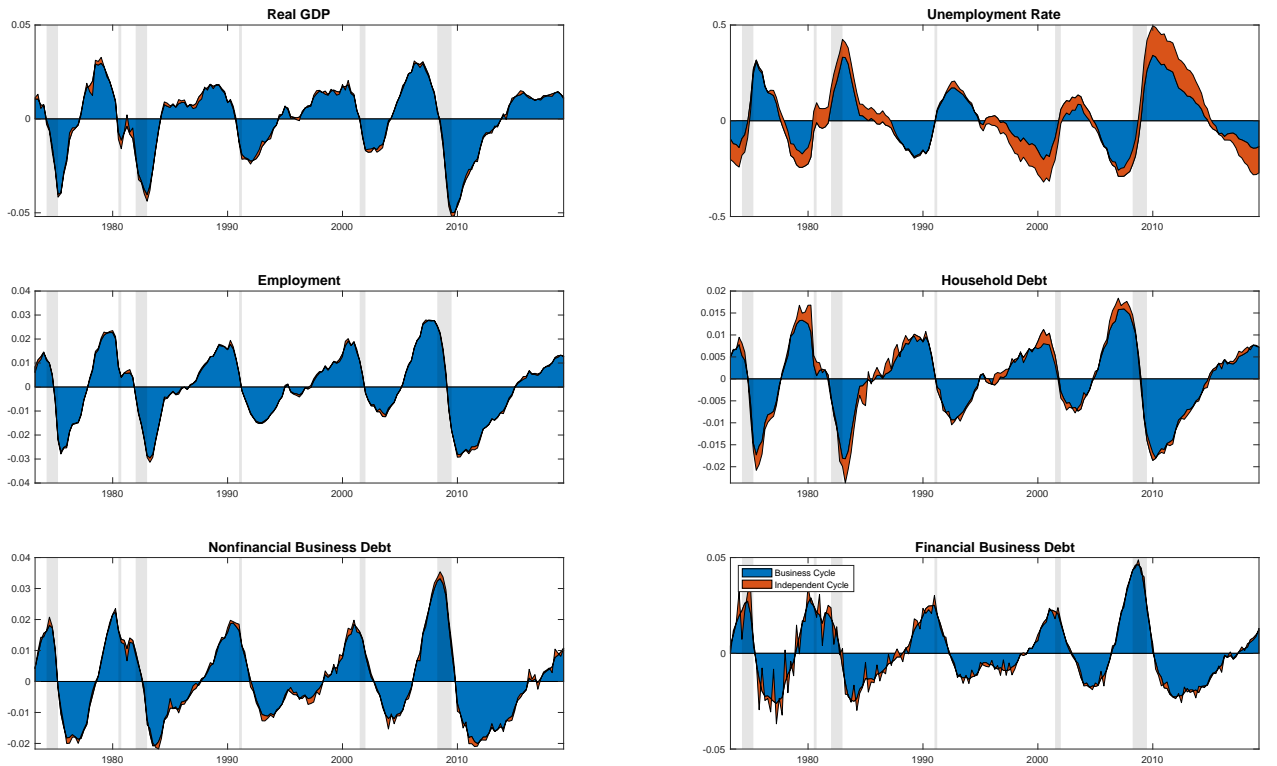
Figure 23 reports the variables in log-levels and their decomposition in variable-specific trends (23a) and cycles (23b), as estimated by the model. A few features are worth highlighting. First, the trends capture the slow-moving components of each variables. Second, the stationary common cycle matches a narrative of recessions which supports its interpretation as the business cycle component, informed by the output gap. Its features match those reported in [Hasenzagl et al. \(2018\)](#) obtained from a model including macroeconomic variables only estimated for a shorter time period. Interestingly, it explains a sizeable portion of the fluctuations of credit variables off trend – with lagging and pro-cyclical dynamics. The idiosyncratic cycles in real and credit variables are very small and may capture small misspecification in the model.

Figure 24 plots the common and idiosyncratic drifts. The output trend growth, i.e. the drift that is common to all the variables, is positive and quite stable over the sample even though it shows a protracted lower growth in the period post financial crisis. The idiosyncratic drifts of debt variables show several persistent deviations from equilibrium relationships in our sample that can be thought of as as measures of ‘excess leverage growth’ in each sector. In particular, plots in Figure 24 show that (i) household debt had two moments of excess debt growth, one in the

¹²We adopt either uniform priors over the range of parameters compatible with our modelling choices or weakly informative priors in the form of Inverse-Gamma distributions.



(a) Variable-specific trends.



(b) Cycle components.

Figure 23: Historical decomposition of the variables in trends and cycles, as estimated by the model. The charts reports the Business Cycle (in blue) and the independent cycle (in red).

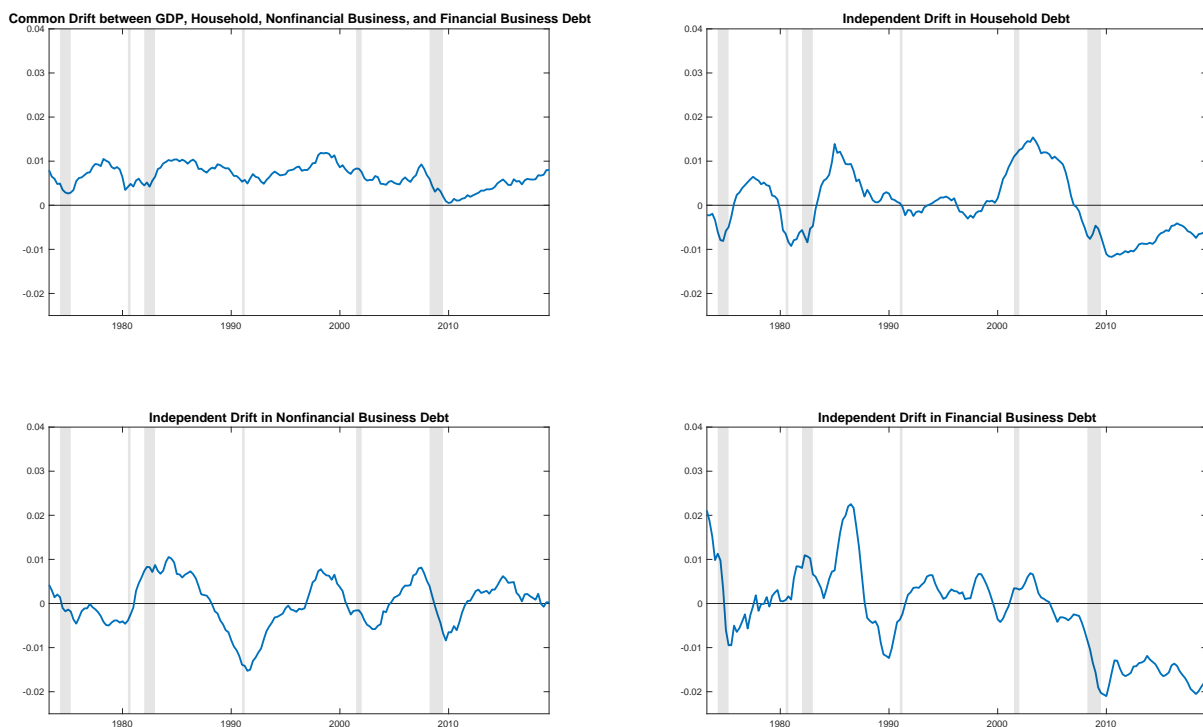


Figure 24: Common and independent drifts, as estimated by the model.

eighties and the other in the first eight years of the new millennium; (ii) nonfinancial debt excess leverage growth followed the two recessions in the eighties and adjusted in the second part of the eighties and in the first half of the nineties; (iii) financial business debt grew in an anomalous manner during the eighties with a peak in mid eighties and a large negative adjustment after the Great Recession. The excess leverage growth episodes in the eighties are likely to be associated to the deregulation of interest rate in banks' deposits (Regulation Q) and to the crisis of the Savings & Loans institutions.¹³

To provide a clearer interpretation of the credit dynamics captured by the idiosyncratic drifts, Figure 25 shows their cumulated values. Cumulated values are better indicators of the build-up of excess leverage in the economy. They capture persistent fluctuations in the credit variables off the (long-run) equilibrium growth of GDP. Conceptually they should be interpreted as the Basel gap, that is as the gap between the current and the long-run credit-to-GDP ratio. However, it is important to stress that these measure are not affected by business cycle fluctuations.

The charts in Figure 25 show three features. First, household debt presents a build-up of excess leverage in the decade preceding the great financial crisis while for the nonfinancial business sector, the excess leverage is a feature of the eighties and follows chronologically the hike in interest rates of Volcker disinflation. Second, for both households and nonfinancial business, our measure of excess leverage point to a small deviation from equilibrium trend in the last few years, reflecting severe deleveraging in the household sector post crisis and a persistent adjustment in the nonbusiness sector since the early nineties. Third, a slow and very persistent accumulation of

¹³Regulation Q is a Federal Reserve regulation which sets out capital requirements for banks in the US. Previously existent caps on interest rates were phased out during the period 1981-1986 by the Depository Institutions Deregulation and Monetary Control Act of 1980.

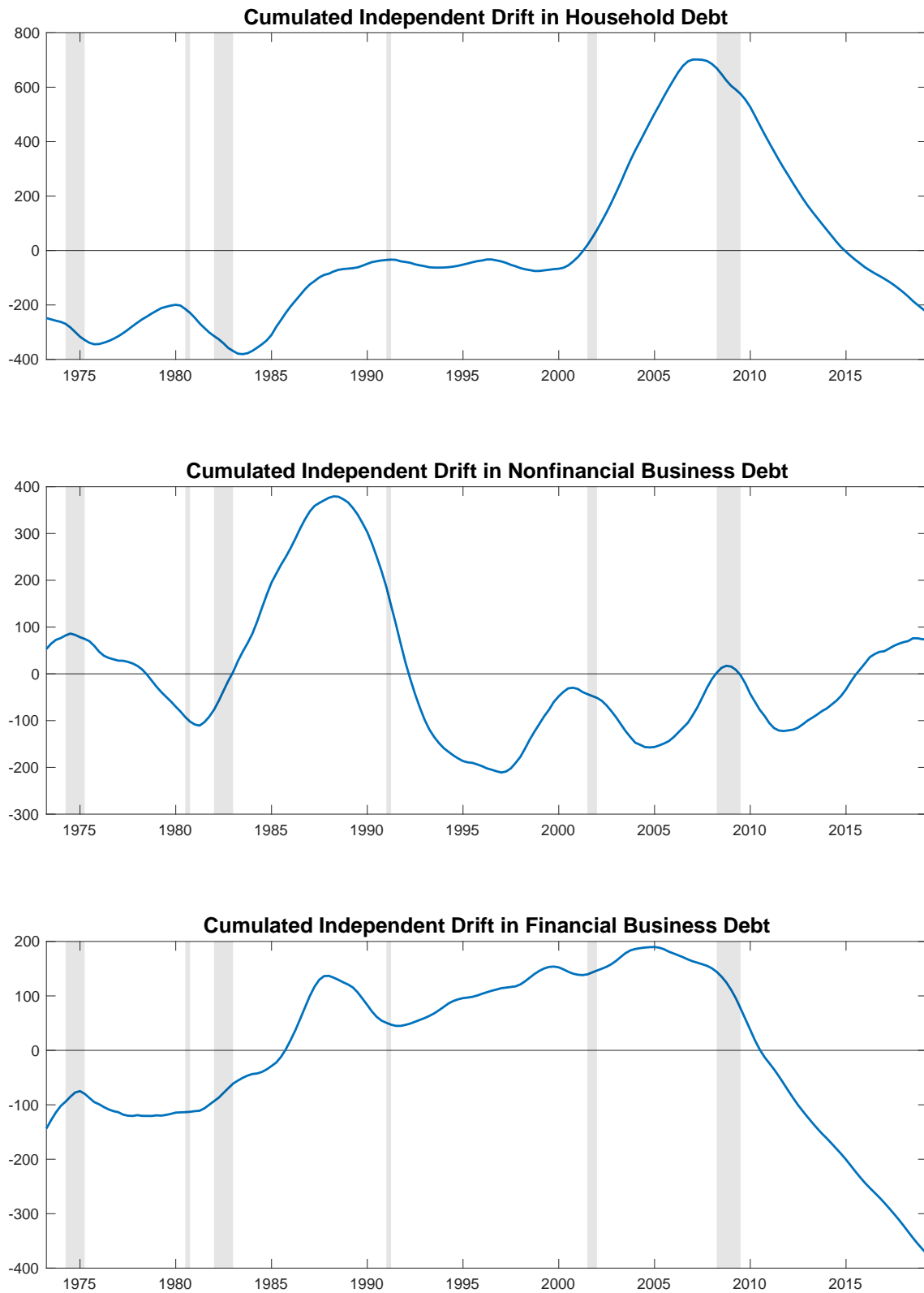


Figure 25: Cumulated idiosyncratic drifts of households', nonfinancial business', and financial business' debt. All variables are in billions of 2012 US Dollars.

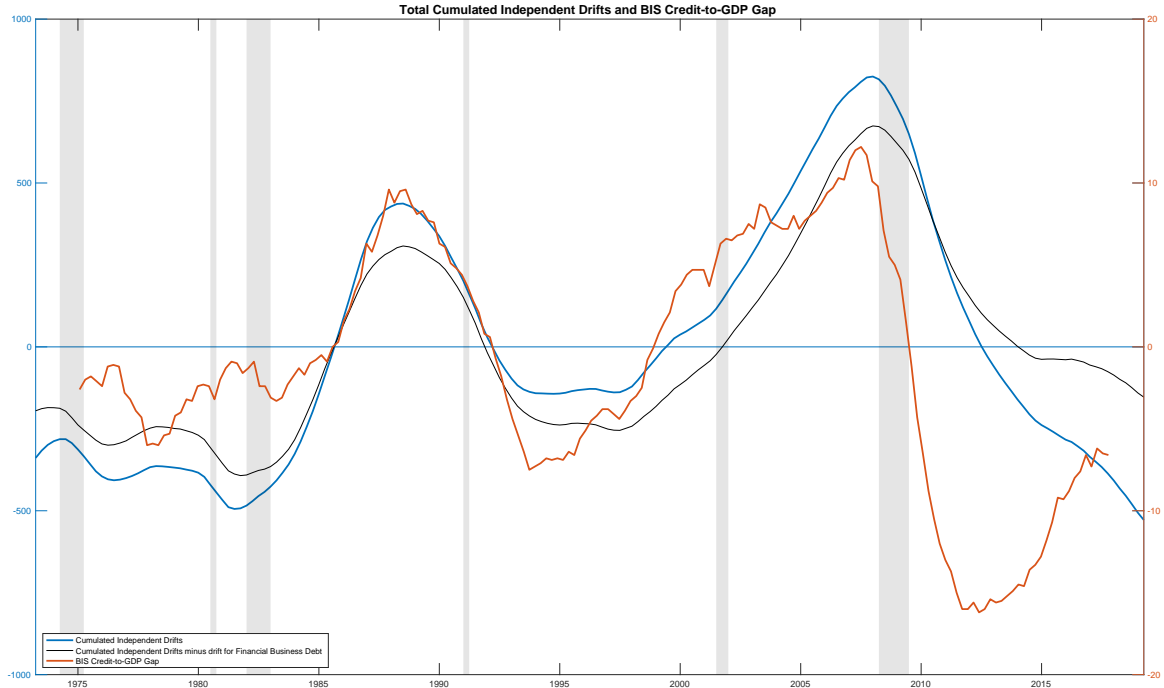


Figure 26: Sum of the cumulated drifts with and without financial leverage, and the BIS Credit-to-GDP Gap.

excess leverage in the financial sector emerged in the mid eighties. Following this accumulation, a severe and persistent deleveraging started just before the 2008 crisis and has led the sector to a historically low level of excess leverage. These features point to a complex narrative in which there is no clear relationship between episodes of leverage accumulation and recessions. Indeed, in the eighties the accumulation of excessive leverage in both financial and nonfinancial business sector followed the twin recessions in the early years of the decade rather than preceding them. These features point to a complex narrative in which there is no univocal causal link between leverage and recessions.

When cumulating and aggregating across variables we obtain a measure that can be interpreted as ‘excess leverage’, in line with the Basel gap. In Figure 26, we report two measures: one obtained by aggregating all the three debt components and one constructed aggregating only household and nonfinancial debt, while excluding financial leverage. The latter is closer to the Basel gap in terms of its definition. These measures point to two phases of excess leverage in our sample – the first in the eighties and the second in the first eight years of the new millennium, before the great recession in 2008. Since then there is a large and persistent correction. The accumulation of leverage in the eighties is mainly due to the financial and nonfinancial business sectors and is likely to be due to interaction between Volcker disinflation, two severe recessions and depository institutions deregulations which eventually led to the Saving & Loans Institutions and to higher financial leverage. The second peak is instead a well known feature of the households excess leverage that started accumulating in the new millennium and preceded the Great Financial Crisis.

When compared to the Basel gap, our index provides a similar picture on the accumulation of debt in the US economy, albeit they are smoother since not affected by business cycle fluctuations. Importantly, our indicator obtained from household and nonfinancial leverage (in line with the Basel gap) does not collapse with the recovery post Great Recession. This is instead a feature of the indicator that includes financial debt. In fact, our indicator shows a persistent de-risking after the last recession which is more pronounced when financial leverage is included. We conclude that our proposed measure is a promising indicator to monitor the building-up of financial fragilities and can be used both in its aggregate form as well as in its disaggregate components version to understand heterogeneity across sectors even beyond the simple example we have provided here.

Conclusions

A few main conclusions emerge from our analysis. First, in relating financial and real economic conditions it is important to consider that aggregate indicators of financial conditions mask a great heterogeneity across variables. In particular, while leverage evolves smoothly and it is very persistent, spreads and other measures of risk based on prices are characterised by occasional spikes. We find that the latter variables, which dominate the aggregate index of financial conditions proposed by the Chicago's Fed (the National Financial Condition Index, NFCI), have very limited advance information for the distribution of GDP growth. Although some limited advanced signal can be detected for the variance of GDP growth, spikes of risk are coincident with (or follow) recessions. Nonfinancial leverage, on the other hand, provides some advanced warning on the left quantile of GDP growth distribution but this is limited to the 2008 crisis.

Second, the analysis of a semi-structural trend-cycle model including disaggregated leverage variables and macroeconomic variables warns us against believing in regularities between leverage accumulation and GDP dynamics. Indeed we find that our measure of excess leverage, which can be interpreted in the same way as the Basel gap, points to a complex narrative. In our sample of US data spanning from the early seventies to 2018, we identify two periods of financial risk related to excess leverage: the eighties and the first eight years of the new millennium. Different sectors, however, behave differently. The eighties is mostly a story of the leveraging up of financial and nonfinancial business related to the interaction between the Volcker disinflation, two severe recessions and financial deregulation while the more recent period is mostly a household story. In the second period the leveraging up of the household sector leads to the Great Recession while in the first there is no leading behaviour of leverage with respect to recessions.

Overall, the broad conclusion of this work is that the relationship between financial variables and real economic conditions is difficult to model. Quantile regressions, which allow for non-linear relationships and therefore offer a flexible method of analysis, do not provide conclusive results while a semi-structural analysis aimed at identifying deviations from long-term equilibria, points to an unstable relationship between excess leverage and GDP growth.

References

- Adrian, Tobias, Boyarchenko Nina, and Giannone Domenico**, “Multimodality in Macro-Financial Dynamics,” Mimeo 2019.
- , —, and —, “Vulnerable Growth,” *American Economic Review*, April 2019, 109 (4), 1263–1289.
- , **Federico Grinberg, Nellie Liang, and Sheherya Malik**, “The Term Structure of Growth-at-Risk,” CEPR Discussion Papers 13349, C.E.P.R. Discussion Papers December 2018.
- Azzalini, Adelchi and Antonella Capitanio**, “Distributions Generated by Perturbation of Symmetry with Emphasis on a Multivariate Skew t -distribution,” *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 2003, 65, 367–389.
- Basel Committee for Banking Supervision**, *Guidance for national authorities operating the countercyclical capital buffer* December 2010.
- Bernanke, Ben**, “The Real Effects of the Financial Crisis,” Technical Report, BPEA Conference Draft, Fall 2018.
- Borio, Claudio**, “The financial cycle and macroeconomics: What have we learnt?,” *Journal of Banking & Finance*, 2014, 45 (C), 182–198.
- and **Philip Lowe**, “Asset prices, financial and monetary stability: exploring the nexus,” BIS Working Papers 114, Bank for International Settlements July 2002.
- Brave, S. and A. Butters**, “Diagnosing the Financial System: Financial Conditions and Financial Stress,” *International Journal of Central Banking*, 2012, 8, 191–239.
- Brownlees, Christian T. and Andre B.M Souza**, “Backtesting Global Growth-at-Risk,” Working Paper 2019.
- Claessens, Stijn, M. Ayhan Kose, and Marco E. Terrones**, “How do business and financial cycles interact?,” *Journal of International Economics*, 2012, 87 (1), 178–190.
- Doz, Catherine, Domenico Giannone, and Lucrezia Reichlin**, “A Quasi-Maximum Likelihood Approach for Large, Approximate Dynamic Factor Models,” *The Review of Economics and Statistics*, November 2012, 94 (4), 1014–1024.
- Drehmann, Mathias and James Yetman**, “Why you should use the Hodrick-Prescott filter - at least to generate credit gaps,” BIS Working Papers 744, Bank for International Settlements September 2018.
- , **Claudio Borio, and Kostas Tsatsaronis**, “Characterising the financial cycle: don’t lose sight of the medium term!,” BIS Working Papers 380, Bank for International Settlements June 2012.
- Figueres, Juan Manuel and Marek Jarociński**, “Vulnerable Growth in the Euro Area: Measuring the Financial Conditions,” Working Paper 2019.
- Forni, Mario, Marc Hallin, Marco Lippi, and Lucrezia Reichlin**, “Do financial variables help forecasting inflation and real activity in the euro area?,” *Journal of Monetary Economics*, September 2003, 50 (6), 1243–1255.

- Gertler, Mark and Simon Gilchrist**, “What Happened: Financial Factors in the Great Recession,” *Journal of Economic Perspectives*, Summer 2018, 32 (3), 3–30.
- Giannone, Domenico, Lucrezia Reichlin, and David Small**, “Nowcasting: The real-time informational content of macroeconomic data,” *Journal of Monetary Economics*, May 2008, 55 (4), 665–676.
- Hamilton, James D.**, “Why You Should Never Use the Hodrick-Prescott Filter,” *Review of Economics and Statistics*, December 2018, 100 (5), 831–843.
- Harvey, Andrew C.**, “Trends and cycles in macroeconomic time series,” *Journal of Business & Economic Statistics*, 1985, 3 (3), 216–227.
- , **Thomas M Trimbur, and Herman K Van Dijk**, “Trends and cycles in economic time series: A Bayesian approach,” *Journal of Econometrics*, 2007, 140 (2), 618–649.
- Hasenzagl, Thomas, Filippo Pellegrino, Lucrezia Reichlin, and Giovanni Ricco**, “A Model of the Fed’s View on Inflation,” CEPR Discussion Papers 12564, C.E.P.R. Discussion Papers January 2018.
- Hatzius, Jan, Peter Hooper, Frederic S. Mishkin, Kermit L. Schoenholtz, and Mark W. Watson**, “Financial Conditions Indexes: A Fresh Look after the Financial Crisis,” NBER Working Papers 16150, National Bureau of Economic Research, Inc July 2010.
- Jorda, Oscar, Mortiz Schularick, and Alan M. Taylor**, “When Credit Bites Back,” *Journal of Money, Credit and Banking*, 2013, 45 (s2), 3–28.
- , **Schularick Moritz, and Alan M Taylor**, “Financial Crises, Credit Booms, and External Imbalances: 140 Years of Lessons,” *IMF Economic Review*, June 2011, 59(2), 340–378.
- Kaminsky, Graciela Laura**, “Currency and Banking Crises; The Early Warnings of Distress,” IMF Working Papers 99/178, International Monetary Fund December 1999.
- Kilian, Lutz and Simone Manganelli**, “The Central Banker as a Risk Manager: Estimating the Federal Reserve’s Preferences under Greenspan,” *Journal of Money, Credit and Banking*, September 2008, 40 (6), 1103–1129.
- Krishnamurthy, Arvind and Tyler Muir**, “How Credit Cycles across a Financial Crisis,” NBER Working Papers 23850, National Bureau of Economic Research September 2017.
- Laeven, Luc and F. Valencia**, “Systemic Banking Crises Database: An Update,” IMF Working Paper 12/163, International Monetary Fund June 2012.
- Lang, Jan Hannes and Peter Welz**, “Semi-structural credit gap estimation,” Working Paper Series 2194, European Central Bank November 2018.
- , **Cosimo Izzo, Stephan Fahr, and Josef Ruzicka**, “Anticipating the bust: a new cyclical systemic risk indicator to assess the likelihood and severity of financial crises,” ECB Occasional Paper Series 219, European Central Bank February 2019.
- Loria, Francesca, Christian Matthes, and Donghai Zhang**, “Assessing Macroeconomic Tail Risk,” Working Paper 19-10, Federal Reserve Bank of Richmond April 2019.
- Monache, Davide Delle, Andrea De Polis, and Ivan Petrella**, “Modeling and Forecasting Macroeconomic Downside Risk,” Mimeo 2019.

- Prasad, Ananthakrishnan, Selim Elekdag, Phakawa Jeasakul, Romain Lafarguette, Adrian Alter, Alan Xiaochen Feng, and Changchun Wang**, “Growth at Risk: Concept and Application in IMF Country Surveillance,” Working Paper Series 19/36, International Monetary Fund February 2019.
- Reinhart, Carmen M. and Kenneth S. Rogoff**, “The Aftermath of Financial Crises,” *American Economic Review*, May 2009, 99 (2), 466–72.
- Repullo, Rafael and Jesús Saurina**, “The Countercyclical Capital Buffer of Basel III: A Critical Assessment,” CEPR Discussion Papers 8304, C.E.P.R. Discussion Papers March 2011.
- Rünstler, Gerhard and Marente Vlekke**, “Business, housing, and credit cycles,” *Journal of Applied Econometrics*, March 2018, 33 (2), 212–226.
- Schularick, Moritz and Alan M. Taylor**, “Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008,” *American Economic Review*, April 2012, 102 (2), 1029–61.
- Stock, James H. and Mark W. Watson**, “Forecasting Output and Inflation: The Role of Asset Prices,” *Journal of Economic Literature*, September 2003, 41 (3), 788–829.