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FINANCIAL CONDITIONS AND 'GROWTH AT RISK' IN ITALY

by Piergiorgio Alessandri[*], Leonardo Del Vecchio[*♠] and Arianna Miglietta[*]

Abstract

This paper studies the relationship between financial conditions and economic activity in Italy using quantile regression techniques in the spirit of Adrian, Boryachenko and Giannone (2019). We exploit the volatility of the 2008-2012 period to assess the plausibility of 'tail' predictions obtained from a broad range of financial indicators. We find that, although spikes in financial distress are typically followed by economic contractions, using this relationship for out-of-sample forecasting is not trivial. To some extent, the models predict the slowdowns experienced by Italy after 2008, but the forecasts are volatile, their quality varies across indicators and horizons, and the predictions tend to overestimate the likelihood of an upcoming recession. As such, these tools represent a complement to, rather than a substitute for, an articulated and diversified systemic risk assessment framework.

JEL Classification: C21, E37.
Keywords: quantile regressions, financial conditions, growth risk.

Contents

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1. Introduction*

The Global Financial Crisis gave new impetus to the research on the linkages between financial markets and real economy. The mechanisms through which financial markets can trigger or amplify business cycle fluctuations have been investigated by economists for a long time[1]. The experience of the last decade, however, has drawn attention to the possibility that the financial accelerator operates in a highly non-linear way, and that financial markets might be prone to 'crises' that generate sharp, long-lasting recessions rather than ordinary business cycles[2]. After the introduction of Basel III, this possibility has become extremely relevant for macroprudential authorities tasked with preserving the resilience of the financial sector and the stability of credit markets.

This paper studies the nexus between financial and real economy from a predictive angle, asking whether distress in financial markets systematically anticipates downside risks for economic growth over the short or medium term. Following Adrian, Boryachenko and Giannone (2019), we estimate a set of predictive quantile regressions where future economic activity is linked to current financial conditions, measured through a set of alternative market- or bank-related indicators. The quantile regression setup allows us to model the relation between financial markets and real economy in a flexible way, allowing for the possibility of a stronger correlation arising in bad times. One of its key advantages is that no restrictions are imposed *a priori* on the nature of these non-linearities. The regressions are estimated using Italian data up to December 2018. The sample includes the aftermath of the Global Financial Crisis of 2008-2009 (GFC) and the European sovereign debt crisis (SDC) of 2011-2012, which provide a natural testing ground for models that focus on 'tail' predictions.

Our results confirm that the correlation between financial conditions and economic activity is stronger in bad times and that spikes in financial distress provide useful information on tail risks for the real economy. This finding holds for a broad range of indicators. Interesting differences emerge between market-based variables, that perform best over short forecasting horizon, and credit-based variables, such as the credit-to-GDP gaps computed following the Basel III prescriptions, that perform well at horizons of one year or more. Using the regressions based on the Bank of Italy's Financial Condition Index (FCI), we construct two summary statistics of macroeconomic risk: a forward-looking "recession probability" that quantifies the likelihood of observing a contraction in output over the next 12 months and an "uncertainty" indicator that captures the dispersion of the one-year-ahead forecasts. Both measures peak during the GFC and the SDC, suggesting that policy makers could have exploited the models to anticipate the macroeconomic volatility triggered by the crises. These

* This work has benefited from feedback by Fabio Busetti, Michele Caivano, Davide Delle Monache, Antonio Di Cesare, Giorgio Gobbi, Claudia Pacella and seminar participants at the Bank of Italy. All remaining errors are our own. The views expressed in the articles are those of the authors and do not involve the responsibility of the Bank.

[1] See e.g. Jermann and Quadrini (2012), Gilchrist and Zakrajsek (2012) and the references therein.

[2] He and Krishnamurthy (2012), Brunnermeier and Sannikov (2014).

results, however, come with three important caveats. First, the performance of the models is not stable across indicators, horizons and estimation periods. Second, the forecasts are volatile. Third, the models appear to over-predict the likelihood and severity of bad outcomes, generating 'false positives' on the occurrence of future contractions in economic activity.

The relatively lacklustre performance of the indicators is likely to reflect a combination of different factors. Some are structural: the markets for private securities are traditionally smaller and less liquid in Italy compared to the US, implying that price dynamics might be generally less informative and less relevant for the real economy. Others are historical. The introduction of the Euro and the switch to a new monetary policy framework in the early 2000s presumably caused a significant shift in the relation between financial and real outcomes. The exceptional monetary and fiscal initiatives of the post-2008 era might also partly explain the overestimation of tail risk observed in most of our specifications: these policy interventions, which played a significant role in mitigating the impact of the crises, could hardly be anticipated on the basis of the historical evidence. All in all, the evidence suggests that the forecasts are not sufficiently reliable to be used as a direct input for macroprudential policy decisions. Our tentative conclusion is that the estimates can in principle provide useful information to macroprudential authorities, but they should be used critically within a risk assessment framework that relies on a rich and well-diversified information set.

1.1 Related Literature.

The forecasting problem examined in this paper is not new. However, the relation between financial variables and macroeconomic aggregates has been traditionally investigated using point forecasts and linear models (Stock and Watson, 2003; Stock and Watson, 2012; Ng and Wright, 2013). Relatively few papers analyze the issue from a distributional perspective. De Nicolò and Lucchetta (2017) show that quantile regressions generate reliable estimates of real and financial risk for the US economy up to a one-year horizon. Alessandri and Mumtaz (2017) construct density forecasts using non-linear models that explicitly capture the amplification effects arising from financial frictions and borrowing constraints, such as Threshold or Markov-switching VARs. Giglio et al. (2016) find that financial condition indices can explain unexpected fluctuations in output and inflation, obtained as the residuals from a first-stage linear forecasting model. Adrian, Boryachenko and Giannone (2019, henceforth ABG) propose a two-step procedure where predictive densities for GDP growth are obtained by first fitting quantile regressions and then interpolating the quantiles using a flexible functional form. Their conclusion is that tighter financial conditions are associated with both a decline in the conditional mean of GDP growth and an increase in its volatility, with no effects for the upper quantiles of the distribution. The results open the way to the calculation of "growth at risk" statistics that link the likelihood of an economic downturn to the current state of financial markets. Indicators inspired by ABG are currently published by a number of public institutions (see e.g. IMF (2017) and ECB (2018)).

The remainder of the paper is organized as follows. Section 2 illustrates the design of the quantile regressions. Section 3 describes our dataset and provides preliminary evidence on the nonlinearity of the relation between economic activity and financial indicators. Section 4 carries out an extensive out-of-sample forecasting exercise, assessing the performance of alternative financial indicators based on (various combinations of) asset prices, spreads, volatilities and credit stocks. Section 5 studies in more detail the forecasts obtained with the Bank of Italy's Financial Condition Index. Section 6 concludes.

2. Empirical set-up.

The basic tool employed in this paper is a quantile regression that links future economic activity (EA) to its current value and some measure of financial conditions (FC):[3]

$$\mathbb{Q}(\, EA_{t+h} |\, \mathcal{I}_t\,) = \alpha_q + \beta_q EA_t + \gamma_q FC_t \qquad (1)$$

Economic activity is represented alternatively by GDP, industrial production or Itacoin, a model-based coincident indicator of the business cycle. The latter is used in levels, while for GDP and IP we use cumulative growth rates over the forecasting horizon h. For each EA measure we test a broad set of candidate financial condition indicators based on market data and/or credit aggregates (see Section 4). We consider forecasting horizons of h = 1, 2, 3, 4, 8 quarters and estimate the regressions for all deciles of the distribution as well as two more extreme 'tail' quantiles, i.e. 5% and 95%. The specification of the regression closely resembles that used by ABG; robustness tests suggest that introducing more lags of the dependent variable does not improve the performance of this simple model (the details are available upon request). The focus of our analysis is on the out-of-sample performance of the regressions. Unless otherwise stated, we use data up to December 2005 as a training sample and start forecasting from January 2006; the forecasts are computed recursively adding one observation at a time.[4] The starting point of the training sample varies between 1970 and 1993 depending on data availability (see Section 4).

To study the unconditional calibration of the forecasts we use *Probability Integral Transforms* (PITs, see e.g. Andersen et al., 2003). These check whether on average the predictions match the

[3] Koenker & Hallock (2001) survey quantile regressions; Komunjer (2013) discusses their use for forecasting.
[4] The starting point of the training sample varies between 1970 and 1993 depending on data availability (see Section 4).

unconditional distribution of the data; in particular, the forecasting model is "well-calibrated" if the number of predictions falling below any given quantile *x* represents approximately *x%* of the sample. The accuracy of the forecasts and the predictive power of the financial indicators is examined by calculating *quantile* R^2 statistics similar to those used by Giglio et al. (2016). This metric compares the prediction errors of a regression to those obtained from an alternative benchmark model, measuring the percentage gain (*quantile* R^2>0) or loss (*quantile* R^2<0) delivered by the model relative to the benchmark across different quantiles and forecasting horizons.[5] We consider two alternative benchmarks. The first one only includes an intercept term and is defined by assuming $\beta_q = \gamma_q = 0$ in equation (1). This benchmark allows us to test the existence of relevant and predictable forms of time variation in tail risk. A failure to beat this model would imply that bad outturns occur with an approximately fixed probability, and cannot be predicted using the cyclical information embedded in EA_t and FC_t. The second one is an AR(1) model of economic activity obtained by setting $\gamma_q = 0$ in equation (1). A comparison between the full model and this benchmark quantifies more directly the marginal informational content of FC_t over and above that included in the latest observation EA_t.

To conclude, it is important to remark that quantile curves are estimated individually. Therefore they can cross, leading to an invalid distribution for the response variable. Constrained versions of the quantile regression have been proposed, e.g. in Bondell et al (2010). The results of this work, however, are not affected by crossing quantiles issues: the quantile grid that we use is coarse and we are not estimating the full probability distribution forecast of our response variables.

3. Data and stylized facts

An overview of the economic activity and financial condition indicators used in the empirical analysis is provided in Table 1. We measure economic activity in Italy using alternatively real gross domestic product (GDP), industrial production (IP) or Itacoin. GDP is the most intuitive measure to appraise broadly the state of the economy. It represents an important input in many policy debates (concerning e.g. fiscal policy or the calculation of aggregate credit-to-GDP ratios), and it is commonly used in growth-at-risk analyses. Data on real GDP growth are quarterly and cover the period 1970q1–2018q3. To complement the information, we also use monthly data on IP growth and Itacoin, a cyclical coincident indicator for the Italian economy derived from a factor model.[6] Due to their monthly frequency, these variables (i) capture in a more timely fashion the release of relevant information on economic developments, (ii) provide larger samples for the estimation, and (iii) allow

[5] Formally, the statistic is the ratio of the averages of the pseudo-forecast errors (transformed through the quantile loss function ρ) obtained from full and restricted quantile regressions: see Giglio et al. (2016) for details.

[6] The construction of Itacoin is discussed in Aprigliano and Bencivelli (2013).

the forecast to be updated more frequently, which might be desirable when deploying the models in the policy arena. IP and Itacoin are in many ways complementary. IP is narrower in scope, though it represents an important component of GDP in terms of value added. Itacoin is broader, it tracks GDP closely and it is very stable, providing estimates that are seldom subject to revisions even during volatile periods (Aprigliano and Bencivelli, 2013). However, to the extent that it is model-based and subject to estimation errors, this indicator might be less reliable than IP growth. The two measures also differ in terms of samples, as Itacoin is only available from 1996. Following ABG, we do not use real-time data and use for all series the vintage available as of May 2019.

To assess conditions in Italian financial markets we use several metrics. We consider both composite indicators of systemic stress that aggregate information from a number of financial markets and simpler indicators that feature regularly in the policy debate and/or have been found to have good leading properties in other studies. The composite indicators include: the Financial Condition Index (*FCI*) developed at the Bank of Italy to monitor the build-up of risks within the Italian system (Miglietta and Venditti, 2019); the sub-components of the FCI related to money and bond markets (*FCI money* and *FCI bond*, respectively)[7]; the Composite Indicator of Sovereign Stress developed by the ECB (*CISS sovr*), which provides a measure of sovereign bond market stress both in the euro area and at the country level (Garcia-de-Andoain and Kremer, 2018); the ECB's Country Level Index of Financial Stress for Italy (*CLIFS*, Duprey et al., 2017); and the Composite Indicator of Systemic Stress in the Euro Area developed by Hollò et al. (2012) (*CISS*). The set of simpler, model-free indicators includes: (i) the spread between 10-year and 1-year Italian sovereign bond yields (*Term Spread*); (ii) the spread between the Italian and the German 10-year bond yields (*Sovereign Spread*); (iii) the option-implied volatilities of the S&P500 and EuroStoxx50's stock price indices (*VIX* and *VSTOXX*); (iv) the interest rates applied on new lending to households or non-financial corporations (*R house, R nfc*); (v) two "credit gap" measures obtained by detrending the ratio of bank credit or total credit to GDP as prescribed by the Basel III regulation (*CGap Bank, CGap Total*)[8].

Before moving to forecasting we briefly explore the relation between economic activity and financial conditions in our data using simple full-sample statistics. Figure 1 shows the output of a univariate regression where year-on-year GDP growth is regressed over a constant and the lagged FCI. In particular, and consistent with the regression analysis in sections 4 and 5, we relate growth

[7] We focus on the bond and money market components of the FCI (excluding the remaining three components, which relate respectively to equity, foreign exchange and financial stocks) because they are less volatile and they have a stronger unconditional correlation with GDP. The bond market component is also the largest one, accounting for 46% of the aggregate index.

[8] The gaps are calculated by applying a Hodrick-Prescott filter with a large smoothing parameters (λ=400,000) to the underlying quarterly credit-to-GDP ratios. We use a variation of the ESRB methodology where the filter is corrected in real-time accounting for its past errors: see Alessandri at al. (2015) for details.

between t and $t+4$ to the FCI level observed at time t. The graph contains a scatterplot of the data, with FCI and GDP respectively on the horizontal and vertical axis, together with the regression lines associated to the 1st, 5th and 9th decile of the distribution. The slopes of the regressions are always negative, indicating that a higher FCI – i.e. tighter financial conditions – anticipates an economic slowdown. However, the slope of the regression changes considerably across the distribution: the regression is nearly flat when growth is positive (red line), mildly negative around the median (green line) and strongly negative for observations located around the 10% tail of the GDP distribution (orange line). In this simple set-up, and based on full-sample information, the leading power of the FCI is indeed much more pronounced in 'bad times', namely in periods of weak or negative growth. This result is fully consistent with ABG, and it is broadly representative of the unconditional relation between economic and financial indicators in our data: similar results hold for IP and Itacoin and for the majority of our financial condition indicators. In fact, the statistical significance of the estimated coefficients is often higher for IP and Itacoin, possibly because of the higher number of observations associated to the monthly frequency of the data. Furthermore, a similar pattern emerges from regressions where lagged economic activity is included among the controls. In short, based on full-sample information one would confidently conclude that 'the tails are different' in terms of dynamics. The key question examined in this paper is to what extent this regularity can be exploited from a forecasting perspective.

4. An overview of alternative forecasting models

This section documents the forecasting performance of a range of alternative quantile regression models. In Section 4.1 we cast the net wide, examining 15 financial indicators, 3 economic activity measures and forecasting horizons that go from 3 to 24 months. Section 4.2 offers a more detailed comparison between FCI and CISS, two aggregate systemic risk indicators that emerge among the most promising options in the horse race.

4.1 Horse races among financial indicators

We estimate quantile regressions for all possible pairs of financial condition and economic activity indicators listed in Table 1. The training sample ends in all cases in December 2005, and the regressions are estimated recursively from that date onwards, with forecasting horizons ranging from 3 to 24 months (1 to 8 quarters in the case of GDP). The regressions are estimated around the deciles of the distribution plus the 5% and 95% quantile. This grid is sufficiently rich to characterize the nonlinearity of interest; for some of the specifications we also estimate the model separately around all percentiles.

It is worth noting that the calibration of the models – i.e. their ability to reproduce the unconditional distribution of the economic activity indicators – is far from perfect.[9] The most common failure is an overestimation of the left tail of the distribution: on average, the models tend to place too many forecasts below the 10th and 20th percentiles of the data. In some instances this also affects the center of the distribution, with more than half of the forecasts falling below the median. A second potential failure is over-dispersion: for some models the distribution of the forecasts has a wider support than that of the underlying data. Taken together, these symptoms suggest that the predictions derived from the financial indicators can be overly volatile and somewhat "pessimistic". We return to these points below and in section 5.

Since we are mainly interested in predicting bad outcomes, we summarize the models' performances using their average R^2 gains for the three lowest quantiles included in our grid, i.e. 5%, 10%, 20%. These probability levels provide a reasonable characterization of 'adverse' scenarios; by averaging three estimates we obtain a statistic that does not hinge too heavily on a specific percentile. In any case, detailed R^2 estimates for all quantiles and horizons are provided in Annex A. Table 2 reports the gains achieved by the models vis-à-vis quantile regressions that only include the intercept. We highlight gains and losses respectively in green and red, using stronger tones for figures that are quantitatively more significant. There is strong evidence of time-variation in "tail risk": most models beat the constant by large margins when it comes to forecasting below-median outcomes, implying that the distribution changes over time in a predictable way. The dark green areas in Table 2 show that, based on our average metric, the R^2 gains range between 20% and 70% and they occur systematically across FC indicators and forecasting horizons. This is not the case for above-median outcomes, for which the models can easily underperform a constant (see Annex A); this reveals that time-variation affects the left tail but not the right tail of the distribution, consistent with ABG. The gains tend to decrease over the forecasting horizon, and the regressions based on monthly data suggest that IP growth is overall less predictable than the (smoother and less volatile) Itacoin.

In Table 3 the analysis is replicated using as benchmark a quantile AR(1) model. The results change dramatically. Controlling for the autoregressive term of the target wipes out most of the gains shown in the previous table. If measured relative to an autoregressive benchmark model, the gains delivered by our baseline regressions are (i) generally much smaller, (ii) less robust across horizons, and (iii) confined to only few of the FC indicators in our set (most notably FCI, CISS and the two credit gap measures). This suggests that many fluctuations in 'tail risk' in the data are actually explained by the dynamics of the economic activity indicators: the persistence of GDP, IP and Itacoin

[9] The brief calibration discussion below is based on Probability Integral Transforms (PITs) calculated for all models and forecasting horizons; the details are available upon request.

changes across the distribution, and these changes are by themselves capable of explaining the tail behavior of these variables. Once the change in persistence is controlled for (by introducing an autoregressive term), the explanatory power of the financial variables for tail outcomes is strongly diminished. We investigate this point further in Figure 2. The figure shows the full-sample estimates of the quantile regression coefficients for the model where Itacoin is regressed on the FCI with a forecasting horizon of 6 months[10]. Panel (a) shows the familiar ABG result: the coefficient of FCI is always negative, but much larger in absolute value at low quantiles (in this case the nonlinearity is most evident below the 20th percentile). However, panel (b) shows that the persistence of Itacoin changes even more dramatically across the distribution: the process is weakly autocorrelated above the 80th percentile, has a persistence of about 0.4 at the median, and becomes borderline explosive below the 10th percentile. Intuitively, this means that recent observations on Itacoin are by themselves informative on the likelihood of an upcoming slowdown in economic activity: Itacoin accelerates when moving downwards, and the model's ability to forecast tail outcomes originates in part from this (systematic, and hence predictable) increase in persistence in 'bad times' as well as a stronger correlation with the FCI. In short, two distinct non-linearities are at play (one involving the relation between Itacoin and FCI, the other the persistence of Itacoin itself) and both contribute to fitting the left tail of the data distribution. The comparison between the R-squared statistics in tables 2 and 3 show that in many of our specifications the second one is quantitatively prominent, while the marginal predictive power of the financial indicators is modest once the autoregressive component is accounted for.

Aside from the generalized reduction in the R-squared gains, table 3 delivers a number of interesting insights. When compared to the autoregressive benchmark, the regressions based on Itacoin and IP give similar results. This means that the higher predictability of Itacoin in table 2 is explained by its higher (and possibly more nonlinear) persistence, not by a stronger association with financial conditions. Among the market indicators, FCI and CISS clearly outperform the alternatives for all three of our target variables. The bond and money component of FCI work reasonably well, but not as well as the composite index. VIX dominates VSTOXX: its performance is comparable to that of FCI and CISS at the 3M horizon, but deteriorates over longer horizons. These implied volatility indicators are valuable in the short term but may not be suited to (macroprudential) policy decisions that have long implementation lags. Among the banking indicators at the bottom of the table, interest rates perform poorly, except at the 3-month horizon, whereas the two credit gaps are good predictors

[10] This specification is an interesting case study because its R-squared gain drops from 37% to zero when controlling for the autoregressive term (see tables 2 and 3). Similar results emerge for many other combinations of financial and economic activity indicators.

of GDP and work mostly if not only at horizons of one or two years. In fact, the predictive power of the credit gaps generally rises rather than declining over *h*. Although attaching a structural interpretation to these regressions is problematic, this result is qualitatively consistent with the BCBS suggestion that credit booms can be good for the real economy in the short-term but spell trouble in the medium and long term.

Taken together, the results in table 3 also suggest that it might be sensible to use a combination of market- and bank-based indicators to estimate risks for growth over different horizons rather than relying on a single predictive model. In our data, however, simple multivariate specifications that include FCI, CISS and the Bank credit gap (i.e. the best performers in table 3) do not deliver systematic improvements relative to the univariate specifications[11]. One reason behind this result is presumably the strong comovement across predictors. The forecasting errors generated by different indicators are strongly correlated, particularly for the quantiles below the median: for the 12-month ahead IP forecasts, the correlation between the residuals generated by FCI and CISS range between 65% and 85%; for GDP, they range between 44% and 82%. In short, the models tend to err in the same direction at the same time, particularly when forecasting bad outcomes. This clearly limits the benefits of using many indicators at once. Two better options could be to combine the indicators into a single factor, as in Giglio et al. (2016), or to combine the predictions obtained from different models. Both impose a price in terms of transparency and interpretability of the results. We leave these developments to future research.

4.2 FCI versus CISS

CISS and FCI are constructed using financial data and similar aggregation methods. The main differences between them (i) the raw indicators used, (ii) the geographical scope, with FCI focusing on Italy and CISS on the Euro Zone, and (iii) the weights used to aggregate the subsector indexes to obtain the composite metric. In particular, FCI attaches a larger weight to the sovereign bond market. These differences are clearly visible in the data and give interesting insights on their performance of the indicators in the regressions. In Figure 3 the annual growth rate of IP is plotted against the 12 month lags of FCI and CISS.[12] More specifically, the black dashed line represents cumulative IP growth over the period *t-12* to *t*, where *t* is the month indicated on the horizontal axis, while red and blue lines represent respectively the levels of CISS and FCI observed in *t-12*. Given this timing

[11] Results on the multivariate specifications are available upon request.

[12] We base the comparison on Industrial Production for two reasons. First, that monthly data are useful to estimate regressions over relatively small time windows (see below), and this makes GDP less attractive than IP or Itacoin. Second, both FCI and CISS perform better for IP than Itacoin (see Table 3). The focus on the 12-month horizon is motivated by its relevance for risk assessment and policy decisions; we discuss this point further in Section 5.

convention, the comovements displayed in the chart exactly match those that exploited in the forecasting regressions with horizon $h=12$. The FCI remains generally flat during the market tensions that follow September 11th 2001. Furthermore, unlike CISS, this indicator places the Global Financial Crisis (GFC, 2007-2008) and the sovereign debt crisis (SDC, 2011-2012) roughly on the same footing. FCI and CISS also diverge at the end of the sample, when Italian markets are affected by political uncertainties that are not shared by the rest of the euro area, but this discrepancy affects their levels rather than the (common) downward trend. The figure suggests that the GFC might play a role in explaining the discrepancy in the average performance of the two indicators: CISS rises sharply from the beginning of 2008, and this allows it to get the timing of the trough in IP in early 2009 almost perfectly right. FCI by contrast rises slowly, and its peak occurs 'too late' for the one-year ahead prediction.

The role of the two crises is investigated in more detail in Figure 4. The figure shows distributions and correlations of the three variables for 9 non-overlapping two-year windows, from 2001-2002 (top left corner) to 2017-2018 (bottom right corner). Each panel reports the scatterplots of FCI and CISS (vertical axis) vis-a-vis output growth (horizontal axis) with the corresponding OLS regression lines. These are similar to the quantile regressions estimated around the 50th percentile of the distribution, and give an idea of how the relation between financial conditions and output changes on average (i.e. in the middle of the distribution) across different time periods. The timing convention is the same as in the previous figure, with FCI and CISS lagged one year relative to the target. To mimic more closely the quantile regression set-up, however, we replace IP growth with a residual obtained from an AR(1) model: this residual captures 'unexpected' growth (net of the AR(1) term), and it is precisely what the financial indicators should help explain. The first row of the figure shows the results for the early 2000s, which are included in the training sample of the quantile regressions examined in the previous section. The correlation with output is null, and potentially wrongly signed for CISS in 2005-2006. This is consistent with the finding that the quantile regressions are approximately flat in the upper half of the distribution (see e.g. figure 1). The middle row of the figure confirms the important role of the GFC. The slope of the regression in 2007/8 is much steeper for CISS and this is clearly due to the upward jump of the indicator, which moves abruptly from average values that are similar to those of the FCI (0.05-0.10) to maxima that are twice as big (0.3 versus 0.15). This pattern disappears during the following two years and is effectively reversed in 2011-2012, when the slope of the regression is steeper for the FCI. The two indicators yield similar results in the 2013-2014 window but diverge again at the end of the sample (bottom row). The relation with output weakens for both indicators and a potential structural break appears for CISS, whose regression slope turns positive around 2015. Indeed, neither of the indicators anticipates the decline in output that takes place towards the end of 2018.

These results offer two useful insights. The first one is that the average track record of an indicator over a fairly long evaluation period (2006-2018) can be affected by a handful of influential data points (GFC and SDC). The second one is that structural stability can be a concern when forecasting growth at risk. The differences between GFC and SDC show that 'not all crises are the same' and that indicators that perform well in some cases may work poorly in other, apparently similar episodes. In our case, CISS captures better the international dimension of the GFC, which originated in the US and subsequently spread to Europe and Italy, while FCI is more successful in picking up the home-grown sovereign debt tensions of 2011 and 2012.

5. Estimating growth risk with the Bank of Italy's Financial Condition Index

In this section we move from model comparisons to an in-depth analysis of the predictions obtained using the Bank of Italy's Financial Condition Index (FCI), a distress indicator used in the Bank's risk assessment activity that also features in its periodical Financial Stability Report (see Bank of Italy, 2019). The appendix provides a complementary set of results for the CISS indicator, which has a comparable performance in the horse race of Section 4. We analyze the performance of FCI using both GDP and Industrial Production growth as targets. GDP is the broadest and most commonly used economic activity indicator, and it allows a direct comparison with the results of ABG. IP is less representative, but it has the non-negligible advantage that the data are more timely and the forecasts can be updated on a monthly basis.[13] We restrict the focus to the 12-month forecasting horizon. This offers a good compromise between the performance of the regressions and the practical relevance of the forecasts for policy purposes: short-term forecasts are typically better, but harder to use for the calibration of macroprudential interventions.

Figure 5 shows the out-of-sample forecast for GDP (top row) and IP (bottom row). The one-year-ahead forecasts are in the right column. We report the one-quarter-ahead forecast in the left column to give a visual gauge of the trade-off between accuracy and relevance mentioned above. In each panel of the figure the target variable (in blue) is plotted against the 10%, 50% and 90% forecasts (in grey, red and green). The sharp contractions experienced by Italy around 2009 and 2011 are clearly visible in all plots despite the difference among the target series. The chart also shows that the timeliness of IP comes at the cost of a much higher volatility, even when the series is filtered computing year-on-year growth rates. At the 3-month horizon the median predictions track the data

[13] We choose IP rather than Itacoin, which is also available on a monthly basis, simply because the predictions are on average more accurate (see table 3) and a raw data series is a safer target than a model-based indicator.

accurately, particularly in the case of GDP. The fit naturally worsens at the 12-month horizon. Recessions and recoveries are still reasonably aligned, but the 'signals' issued by the models in 2008-2009 appear at the same time delayed and overly drastic: the predicted trough in median GDP for instance is about -12% against an actual outcome of -8.5%. The gap is similar but less pronounced for IP. The behavior of the tail predictions is consistent with the evidence discussed in the previous sections. The right tail of the distribution is fairly stable over time, even during recessions. The left tail, for which the dependence on the FCI is stronger, is more volatile and sends a strong warning on the impending economic slowdown both in 2008/9 and 2011/2. The fact that the 10% predictions fall well below the realized GDP and IP outcomes can be interpreted in more than one way. The most obvious one is that the models are not well-calibrated and tend to be overly pessimistic (as indicated by the PITs discussed in Section 4). Another one is that the ex-ante probability of the observed contractions in economic activity was well above 10% and hence, at least in principle, the recessions could have been even more pronounced. Although this argument is clearly speculative, one possibility is that the FCI did not fully reflect the exceptional monetary and fiscal policy initiatives undertaken during the crises, which (i) had no historical precedent and (ii) played an important role in mitigating the contraction.

The forecasts can be easily summarized by calculating forward-looking "recession probabilities" (RPs) that quantify the chances of observing a net contraction in economic activity over a predefined time interval. More formally, given a generic economic activity indicator *EA* and a forecasting horizon h, the recession probability is defined by the following equation: $\mathbb{P}\left(EA_{t+h} < 0 \mid \mathcal{I}_t\right) \cong \frac{1}{99}\sum_{q=1}^{99} \mathbb{I}(\widehat{EA}_{t+h}^{q} < 0)$, where $\widehat{EA}_{t+h}^{q}$ is the forecast for time $t+h$ at the quantile q.[14] The probabilities associated to the 12-month ahead forecasts are plotted in Figure 6. The GDP-based probability, in gray, is overlaid with the IP-based probability, plotted in black. The GDP estimate is quarterly, like the underlying forecasts, and we simply assume it to remain constant within each quarter to obtain the monthly series displayed in the figure. A first fact that stands out from the figure is that the average recession probabilities over the entire 2006-2018 period are high: 40% for GDP and 63% for IP. This result reflects the weakness of the Italian economy over this period but also the wide dispersion of the forecasts across quantiles, which implies that (particularly in the case of IP) a large portion of the distribution is systematically below the zero line. The dynamics are interesting: the RPs swing between 10% and 80-100% over time, and their maxima pick up the actual

[14] For this calculation we re-estimate the models using a finer grid that includes all percentiles of the distribution (0.01 to 0.99). An alternative strategy would consist of (i) interpolating the quantile forecasts to reconstruct the entire predictive density for GDP growth, and then (ii) calculating RPs and other summary statistics using the interpolated pdf (ABG; IMF, 2017). Our solution avoids the interpolation step. Notice that in both cases the RPs are calculated ignoring the estimation uncertainty around the coefficients of the quantile regressions.

recessions in the sample. The summation over quantiles implicit in the calculation delivers a smoother picture of 'growth at risk' compared to the raw forecasts, but volatility remains an issue. There are many instances where the GDP-based probability increases by 10 percentage points or more over one quarter but drops immediately afterwards, suggesting that policy makers should only trust a persistent variation in the indicator. IP provides a good approximation to the low-frequency movements of GDP but its short-run volatility is much higher, raising questions on its use for risk assessment purposes.

As Figure 5 shows, the forecast distributions typically become wider around recessions. A drop in the left tail is often the key driver behind this increase in dispersion (Figure 5, panel iv), but upward movements of the right tail can contribute to it too (Figure 5, panel ii). In essence, abrupt changes in the FCI mark the beginning of periods during which growth becomes *less predictable* as well as being generally *weaker*. This motivates the construction of summary statistics that focus on the uncertainty surrounding the forecasts. We compute two such measures. The first one, "Total Uncertainty" (TU), is defined as the difference between 90% and 10% predictions. This is by construction a symmetric measure that does not discriminate between good and bad outcomes. As such, it is relevant for risk-averse decision makers but potentially less interesting for risk-neutral agents who only care about mean outcomes. The second measure, defined as the distance between the median and the 10% forecast, is a more specific gauge of uncertainty stemming from "Downside Risks" (DR) to the real economy. DR focuses on the tail that matters the most for macroprudential purposes. Notice that both indicators ignore by construction the median path of the economy, and are unaffected by a parallel downward shift of the forecast distribution. The estimated TU and DR series are plotted in Figure 7. Aside from the usual difference in volatility, the profile of TU is qualitatively similar for GDP and IP. The uncertainty around the GDP forecasts is on average 3 percentage points in 2007 (panel *a*). If interrogated one year earlier, the model would have predicted uncertainty to rise to 15 percentage points by the end of 2008 and to 30 percentage points by the end of 2009. These estimates indicate that the confidence intervals around the projections are generally large, and become much larger in bad times. The associated DR indicators quantify the likely contribution of bad outcomes to the overall uncertainty. In the GFC DR accounts for only about ½ of TU: the reason is that the bad scenarios captured by DR are relatively close to the median path, which already includes a strong recession (-12%). In this case the gap between TU and DR captures a wide range of scenarios where growth is negative, but not as bad as in the median projection. The overall dynamics of the uncertainty indicators are similar for industrial production (Figure 7, panel *b*). In this case, however, the forecasts for the upper quantiles of the distribution are more stable, so DR represents the main driver of uncertainty both in normal and in crisis times.

6. Conclusions

This paper studies the relationship between financial conditions and economic activity in Italy using quantile regression techniques in the spirit of Adrian, Boryachenko and Giannone (2019). We estimate a range of predictive models where economic activity is regressed on various measures of financial conditions, including term and sovereign credit spreads, implied stock market volatility, Basel-type ‘credit gaps’ and synthetic indices obtained from larger financial datasets. We then calculate recursive out-of-sample forecasts for the period between January 2006 and December 2018, using the Great Financial Crisis (2008-2009) and the Sovereign Debt Crisis (2011-2012) as a testing ground for the models’ fitness to predict ‘tail’ outcomes.

Our results confirm that the correlation between financial conditions and economic activity is stronger in bad times and that spikes in financial distress often anticipate a slowdown in economic activity. Various complications arise, however, when using this result for out-of-sample forecasting: the relation is not stable over time, the forecasts are volatile, and the models appear to overestimate the likelihood of low or negative growth scenarios. We explore these issues by studying in more detail the forecasts generated by the Bank of Italy’s Financial Condition Index (FCI). Using the output of the quantile regressions, we calculate forward-looking recession probabilities and uncertainty measures that characterize the outlook for GDP and industrial production growth over a one-year horizon. The qualitative behavior of these indicators is appealing, with peaks that roughly coincide with the recessions experienced by the Italian economy after 2008, but high volatility and false positives remain a concern, cautioning against a literal interpretation of the signals issued by the model. Our tentative conclusion is that ‘growth at risk’ estimates can in principle offer useful information to macroprudential authorities, but they should be used within a risk assessment framework that relies on a rich and well-diversified information set.

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Table 1: Economic activity and financial condition indicators.

	Variable	*Starts*	*Ends*	*Frequency*
(A) ECONOMIC ACTIVITY				
GDP	Real GDP growth	1970q1	2018q3	Quarterly
IP	Industrial production growth	1990m1	2018m12	Monthly
Itacoin	Coincident economic activity indicator	1996m9	2018m12	Monthly
(B) FINANCIAL CONDITIONS				
FCI	Financial Condition Index	1998m12	2018m12	Monthly
FCI bond	Bond market component of the FCI	1998m12	2018m12	Monthly
FCI money	Money market component of the FCI	1998m12	2018m12	Monthly
CISS sovr	Composite Indicator of Sovereign Stress	2000m1	2018m12	Monthly
CLIFS	Country Level Index of Financial Stress	1970m1	2018m12	Monthly
CISS	Composite Indicator of Systemic Stress	1999m1	2018m12	Weekly
Term Spread	Spread between 10Y and 1Y IT sovereign bonds	1991m3	2018m12	Monthly
Sovereign Spread	Spread between 10Y IT and DE sovereign bonds			
VIX	Implied volatility of S&P500 stock price index	1991m04	2018m12	Monthly
VSTOXX	Implied volatility of EuroStoxx50 stock price index	1999m01	2018m12	Monthly
R house	Interest rates on new lending to households	1995m1	2018m12	Monthly
R nfc	Interest rates on new lending to non-financial firms	1995m1	2018m12	Monthly
C Gap Bank	Bank credit-to-GDP gap	1980q1	2018q3	Quarterly
C Gap Total	Total credit-to-GDP gap	1980q1	2018q3	Quarterly

Table 2: Performance of the quantile regressions against a constant model.

	GDP					Itacoin					IP				
	3M	6M	9M	12M	24M	3M	6M	9M	12M	24M	3M	6M	9M	12M	24M
FCI	0.40	0.22	0.25	0.26	-0.37	0.63	0.37	0.23	0.12	-0.02	0.23	0.17	0.14	0.16	0.11
FCI bond	0.35	0.27	0.19	0.17	-0.25	0.63	0.37	0.21	0.09	0.06	0.11	0.11	0.07	0.06	0.13
FCI money	0.34	0.24	0.13	0.12	-0.15	0.62	0.37	0.20	0.13	0.03	0.13	0.12	0.10	0.09	0.14
FCI p.c.	0.20	0.08	0.03	-0.02	-0.02	0.61	0.32	0.14	0.02	0.00	0.04	0.04	0.00	-0.04	0.11
CLIFS	0.27	0.21	0.02	-0.09	0.03	0.64	0.39	0.19	0.03	0.00	0.09	0.10	0.04	-0.01	0.07
CISS	0.42	0.33	0.28	0.32	-0.20	0.64	0.41	0.35	0.19	-0.02	0.30	0.26	0.30	0.33	0.22
CISS sovr	0.20	0.07	0.06	0.08	-0.10	0.56	0.24	0.11	0.04	0.01	0.06	0.06	-0.02	-0.01	0.15
Credit Spread	0.29	0.21	0.04	0.01	0.04	0.61	0.36	0.19	0.05	0.03	0.07	0.07	0.03	0.00	0.16
Term Spread	0.11	0.15	-0.02	-0.12	-0.05	0.62	0.36	0.17	0.05	0.03	0.03	0.06	0.00	-0.03	0.11
VIX	0.35	0.26	0.16	0.13	-0.06	0.64	0.37	0.18	0.04	0.07	0.20	0.14	0.10	0.07	0.05
VSTOXX	0.35	0.16	-0.03	-0.09	-0.12	0.61	0.34	0.13	-0.01	0.07	0.14	0.10	0.02	-0.01	0.14
R house	0.34	0.13	0.01	-0.05	0.03	0.63	0.38	0.18	0.02	0.09	0.06	0.06	0.01	-0.02	0.11
R nfc	0.30	0.14	0.03	-0.08	0.02	0.63	0.38	0.19	0.04	0.09	0.06	0.06	0.02	-0.01	0.12
C Gap Bank	0.24	0.26	0.25	0.23	0.26	0.62	0.35	0.17	0.05	0.10	0.05	0.08	0.04	0.02	0.32
C Gap Tot	0.27	0.27	0.22	0.18	0.12	0.62	0.36	0.17	0.04	0.05	0.05	0.09	0.04	0.04	0.27

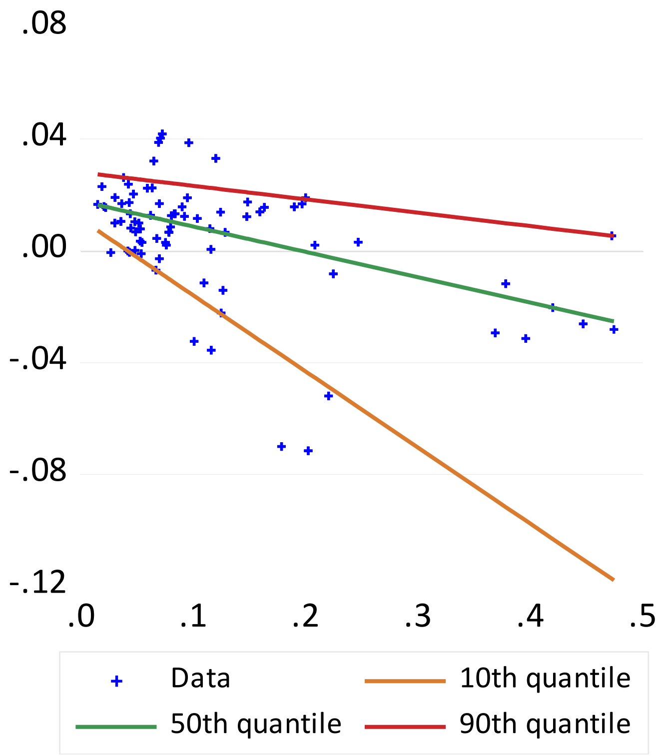
Note: for each Financial Indicator (row) and Economic Activity measure (column), the table reports the predictive R-squared gain obtained by the baseline quantile regression ($EA_{t+h} = a + bEA_t + cFC_t + e_{t+h}$) against a benchmark model that only includes the intercept ($EA_{t+h} = a + e_{t+h}$). The colors go from dark green (R-squared change ≥+20%) to dark red (R-squared change ≤-20%), with yellow cells indicating equivalent performances by the two models (R-squared change ≈0). The horizons (h) range from 3 to 24 months. The R-squared statistics are computed using out-of-sample prediction errors for the period January 2006 – December 2018.

Table 3: Performance of the quantile regressions against an AR(1) model.

	GDP					Itacoin					IP				
	3M	6M	9M	12M	24M	3M	6M	9M	12M	24M	3M	6M	9M	12M	24M
FCI	0.11	0.02	0.19	0.23	-0.32	0.05	0.01	0.07	0.11	-0.07	0.18	0.13	0.12	0.18	-0.05
FCI bond	0.03	0.09	0.13	0.13	-0.21	0.03	0.01	0.05	0.08	0.01	0.05	0.06	0.05	0.09	-0.02
FCI money	0.02	0.05	0.07	0.09	-0.12	0.02	0.01	0.04	0.12	0.00	0.08	0.07	0.08	0.12	-0.01
FCI p.c.	-0.03	-0.04	0.01	-0.03	-0.03	-0.04	-0.08	-0.04	0.00	-0.03	-0.02	-0.01	-0.02	0.00	-0.01
CLIFS	0.01	0.06	0.03	0.00	0.03	0.05	0.03	0.02	0.00	-0.03	0.03	0.05	0.03	0.01	-0.03
CISS	0.14	0.22	0.27	0.35	-0.19	0.07	0.11	0.25	0.20	-0.05	0.27	0.21	0.30	0.35	0.06
CISS sovr	-0.13	-0.07	0.07	0.11	-0.22	-0.08	-0.11	0.02	0.06	-0.05	0.01	0.01	-0.02	0.03	-0.05
Credit Spread	0.04	0.04	-0.04	-0.04	0.04	-0.02	-0.01	0.02	0.02	-0.01	0.01	0.00	0.02	0.03	0.08
Term Spread	-0.12	-0.02	-0.11	-0.17	-0.07	-0.01	-0.02	0.00	0.03	0.00	-0.03	0.00	-0.01	0.00	0.03
VIX	0.13	0.10	0.08	0.09	-0.05	0.05	0.00	0.00	0.01	0.03	0.16	0.07	0.09	0.09	-0.05
VSTOXX	0.04	0.01	-0.03	-0.03	-0.12	-0.01	0.00	-0.01	0.00	0.04	0.10	0.03	0.02	0.02	-0.04
R house	0.17	0.03	-0.01	-0.06	0.02	0.02	0.01	0.02	0.00	0.06	0.01	0.00	0.00	0.00	0.00
R nfc	0.14	0.04	0.01	-0.08	0.01	0.02	0.01	0.02	0.02	0.06	0.01	0.01	0.01	0.01	0.01
C Gap Bank	0.03	0.07	0.12	0.17	0.24	0.00	-0.03	0.00	0.03	0.07	-0.01	0.03	0.04	0.05	0.26
C Gap Tot	0.07	0.09	0.08	0.11	0.10	0.00	-0.02	0.00	0.02	0.02	-0.01	0.03	0.04	0.07	0.20

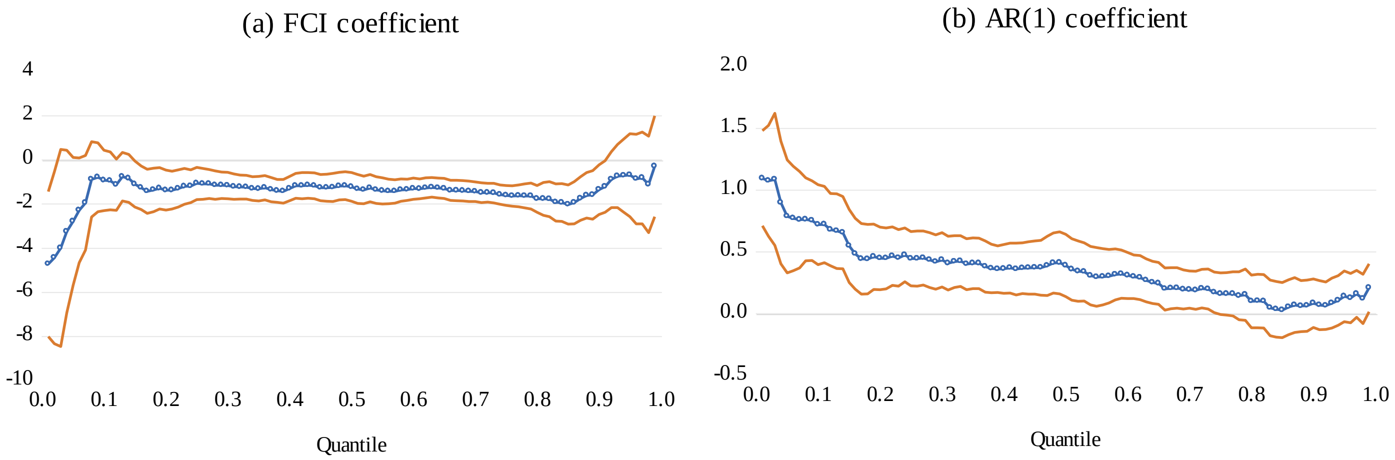
Note: for each Financial Indicator (row) and Economic Activity measure (column), the table reports the predictive R-squared gain obtained by the baseline quantile regression ($EA_{t+h} = a + bEA_t + cFC_t + e_{t+h}$) against a benchmark model that includes intercept and autoregressive term ($EA_{t+h} = a + bEA_t + e_{t+h}$). The colors go from dark green (R-squared change ≥+20%) to dark red (R-squared change ≤-20%), with yellow cells indicating equivalent performances by the two models (R-squared change ≈0). The horizons (h) range from 3 to 24 months. The R-squared statistics are computed using out-of-sample prediction errors for the period January 2006 – December 2018.

Figure 1 – Tail correlation between annual GDP growth and lagged FCI.



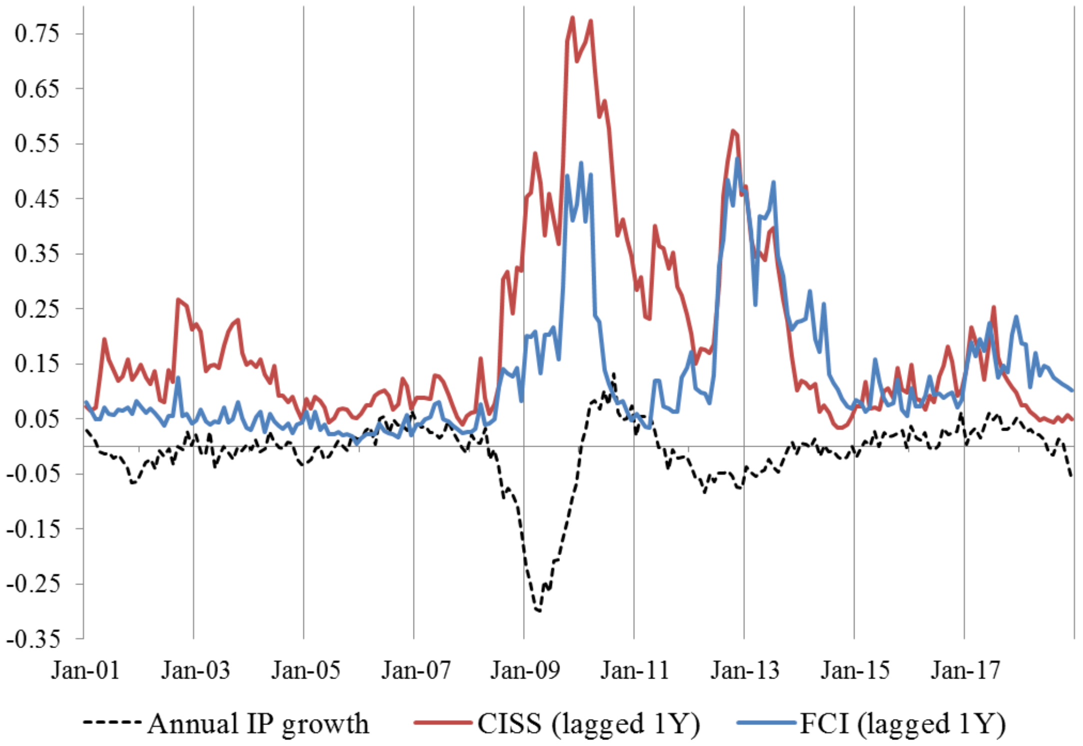
Note: annual GDP growth (vertical axis) versus lagged Financial Condition Index (FCI, horizontal axis). Growth is measured between quarter *t* and quarter *t+4*, while the FCI is measured at time *t*. Orange, green and red lines represent three univariate quantile regressions fitted respectively around the 10th, 50% and 90th percentiles of the distribution. The estimation period is 1998-2018.

Figure 2 – Quantile regression coefficients: correlation with FCI versus persistence.



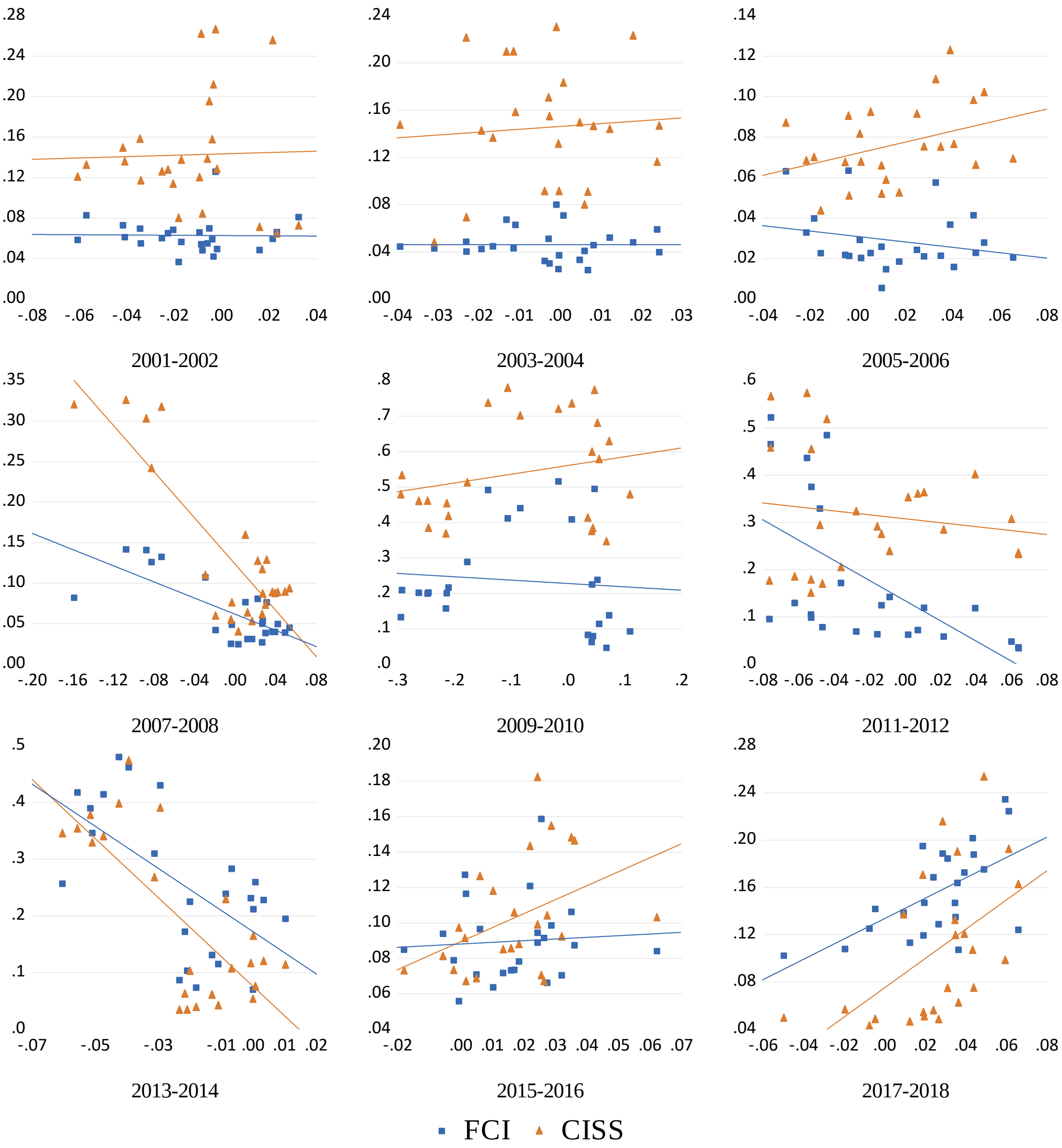
Note: the chart shows the estimated quantile regression coefficients from the model $Itacoin_{t+6} = a + bItacoin_t + cFCI_t + e_{t+h}$. Panel (a) and panel (b) show respectively the estimates of the FCI coefficient (*c*) and the autoregressive coefficient (b), with a 95% confidence band. The quantiles are reported on the horizontal axis. The estimation sample is 1998-2018.

Figure 3 – Industrial Production growth versus lagged CISS and FCI



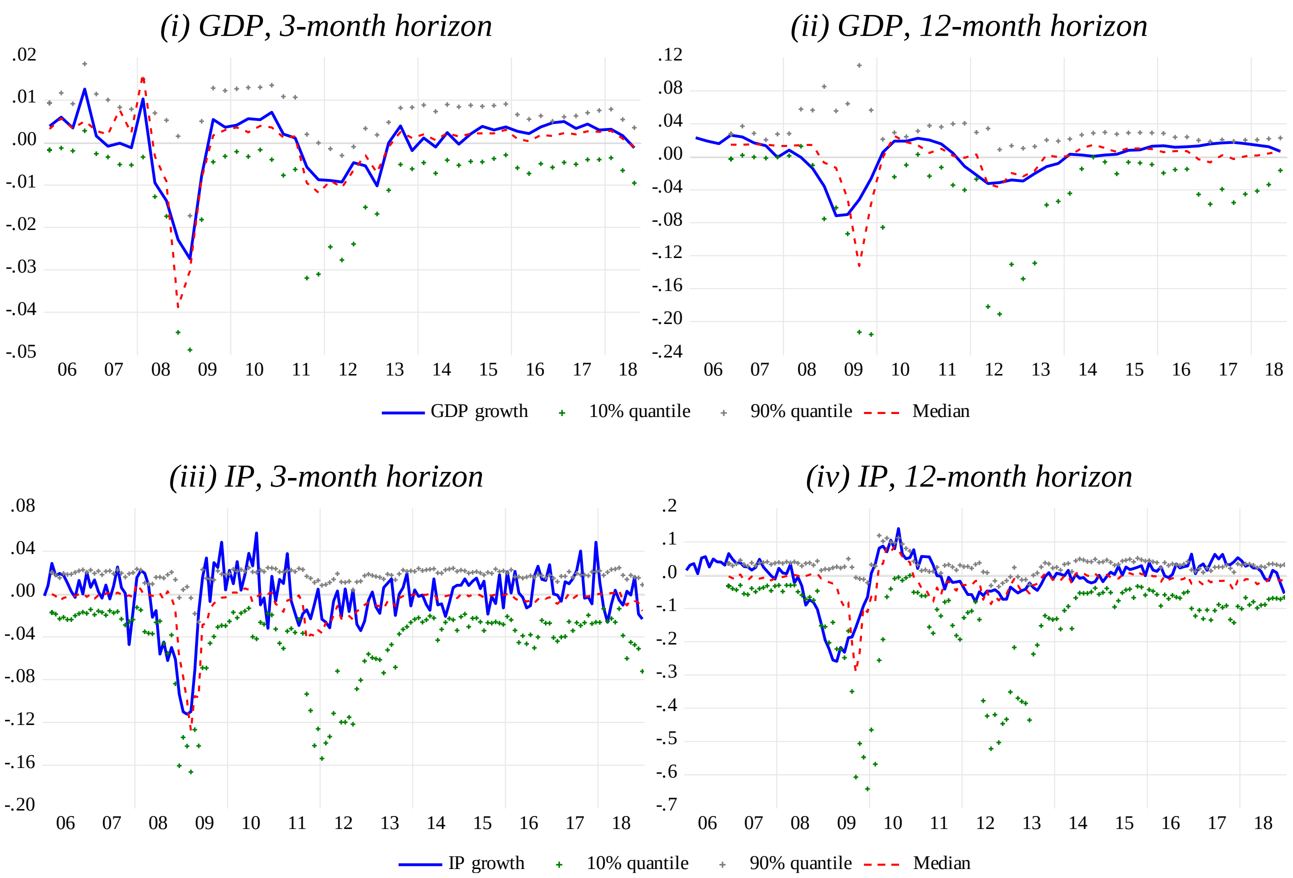
Note: the chart shows the annual growth rate of industrial production (black dashed line) vis-a-vis the lagged CISS and FCI indicators (red and blue lines). IP growth is computed over the 12-month window ending in the month displayed on the horizontal axis, while FCI and CISS are measured 12 month prior to the month displayed on the horizontal axis. This timing convention associates to each IP growth observation the levels of FCI and CISS that would have been used to forecast it one year earlier.

Figure 4 – CISS and FCI regressions estimated over non-overlapping subsamples.



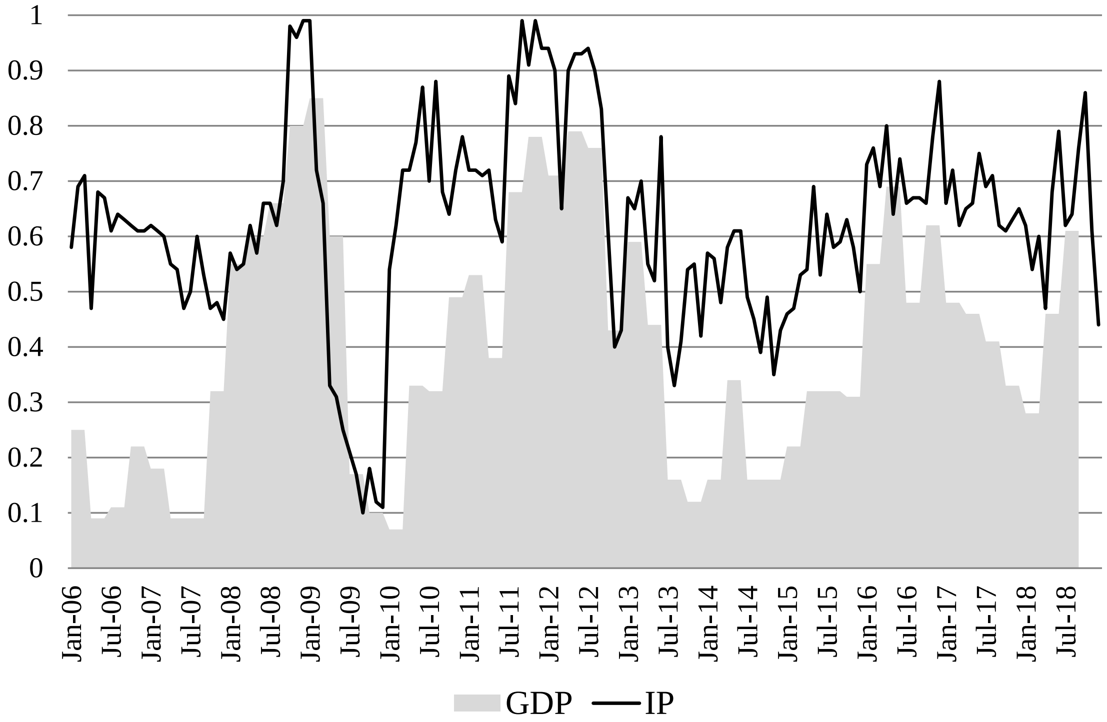
Note: each plot shows the the relation between FCI and CISS (vertical axis) and a measure of "unexpected" annual growth in industrial production (horizontal axis). Unexpected growth is the residual of an AR(1) model fitted to the annual growth rate of industrial production. FCI and CISS are lagged by 12 months relative to growth (See note to figure 3). Each plot refers to a different two-year time windows, from 2001/1-2002/12 (top left corner) to 2017/1-2018/12 (bottom right corner), and displays the distribution of the data and OLS regression lines.

Figure 5 – Out-of-sample quantile forecasts based on the FCI



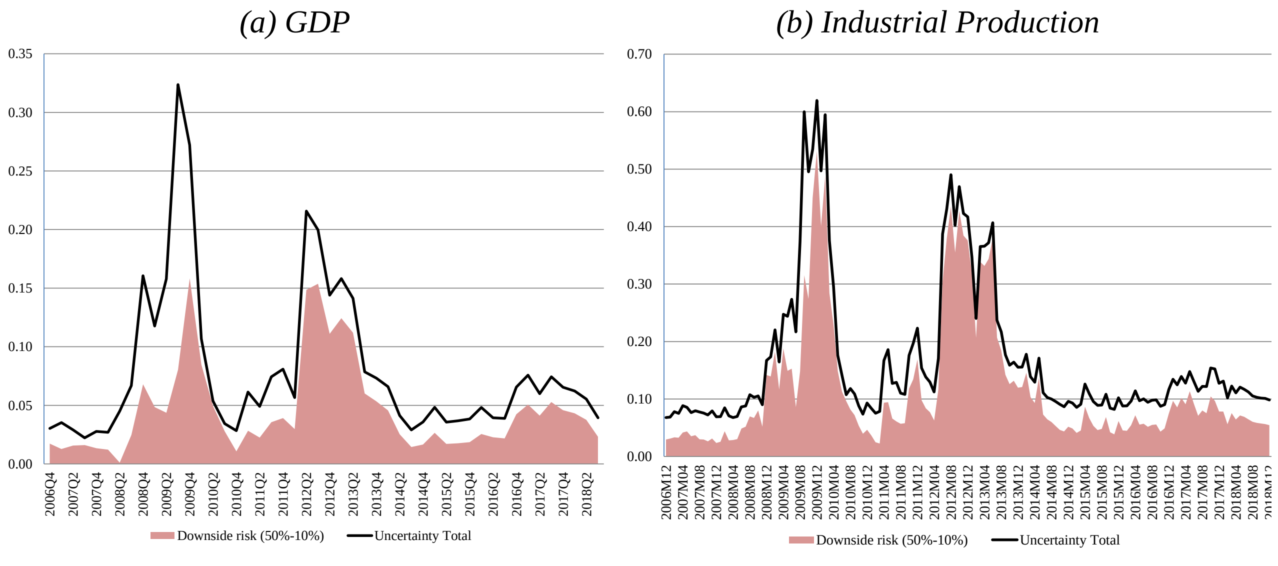
Notes: out-of-sample growth forecasts obtained using the Financial Condition Index (FCI). The forecasts are calculated for GDP growth (top row) and Industrial Production growth (bottom row), considering alternatively horizon of 3 months (left column) and 12 months (right column). In each panel the blue line represents the data, the red dashed line the median forecast, and grey and green dots the forecasts for the 90th and 10th percentile of the distribution. Data and forecasts are quarterly in the case of GDP and monthly in the case of IP. All estimates are based on the quantile regression model described in equation (1). The forecasts are generated recursively, using a training sample that runs from December 1998 to December 2005 and adding one observation at a time.

Figure 6 – One-year-ahead recession probabilities based on the FCI



Notes: the chart shows the model-implied probability of observing a contraction in GDP (grey area) or IP (black line) over the 12-month period ending at the date shown on the horizontal axis. The probabilities are obtained by (i) estimating the quantile regression in equation (1) separately for all percentiles of the data distribution; (ii) generating recursive out-of-sample forecasts for each percentile; and (iii) cumulating the percentiles for which the forecast is negative. See note to figure 5.

Figure 7 – Uncertainty surrounding the one-year ahead economic activity forecasts.



Notes: the chart shows two measures of uncertainty associated to one-year-ahead forecasts for GDP (panel a) and Industrial Production (panel b). *Total Uncertainty* (*Downside Risk*) is defined as the difference between the 90th percentile forecast (50th percentile forecast) and the 10th percentile forecast. All forecasts are obtained from the quantile regression model in equation (1). See notes to Figure 5.

Annex A: Additional Tables

Table A.1: GDP regressions, predictive R^2 gains versus constant (selected indicators)

τ	*0.05*	*0.1*	*0.2*	*0.3*	*0.4*	*0.5*	*0.6*	*0.7*	*0.8*	*0.9*	*0.95*
FCI											
3M	0.467	0.419	0.310	0.274	0.239	0.125	0.087	-0.081	-0.191	-0.045	0.117
6M	0.277	0.207	0.185	0.156	0.127	0.139	0.082	-0.129	-0.189	-0.240	-0.747
9M	0.311	0.243	0.190	0.209	0.164	0.064	0.052	-0.057	-0.234	-0.036	-0.120
12M	0.370	0.195	0.212	0.134	0.138	0.094	-0.061	-0.073	-0.233	-0.041	0.011
24M	-0.880	-0.150	-0.090	0.013	-0.018	-0.052	-0.072	-0.239	-0.216	-0.295	-0.250
FCI bond											
3M	0.331	0.383	0.347	0.322	0.231	0.138	0.127	0.076	0.036	0.053	0.092
6M	0.401	0.198	0.211	0.122	0.073	0.077	0.039	0.040	-0.046	-0.186	-0.664
9M	0.233	0.206	0.136	0.113	0.053	0.033	0.017	-0.028	-0.011	-0.121	-0.031
12M	0.170	0.175	0.158	0.119	0.065	0.049	-0.004	-0.042	-0.100	-0.092	-0.021
24M	-0.451	-0.189	-0.097	0.074	0.088	0.078	0.007	-0.024	-0.057	-0.075	-0.344
CISS											
3M	0.456	0.455	0.361	0.342	0.260	0.120	0.086	0.045	-0.069	-0.502	-0.258
6M	0.378	0.402	0.216	0.158	0.093	0.024	-0.045	-0.026	-0.148	-0.375	-0.605
9M	0.272	0.344	0.209	0.164	0.093	0.024	-0.097	-0.159	-0.348	-0.343	-0.804
12M	0.326	0.359	0.264	0.131	0.023	-0.042	-0.149	-0.185	-0.480	-0.404	-0.578
24M	-0.609	-0.041	0.051	0.105	0.076	0.020	-0.068	-0.090	-0.236	-0.439	-0.927
Credit Spread											
3M	0.321	0.258	0.286	0.231	0.195	0.175	0.178	0.186	0.126	0.114	0.123
6M	0.274	0.237	0.116	0.118	0.109	0.120	0.089	0.076	0.041	-0.014	0.066
9M	0.035	0.093	0.002	-0.027	0.048	0.074	0.056	-0.009	0.012	0.029	0.036
12M	0.072	-0.015	-0.022	-0.011	0.015	0.003	0.005	-0.026	-0.047	-0.063	0.046
24M	0.128	0.028	-0.043	-0.034	-0.022	-0.014	-0.043	-0.043	-0.054	-0.039	-0.062
VIX											
3M	0.418	0.322	0.317	0.275	0.211	0.169	0.140	0.145	0.109	0.010	0.001
6M	0.295	0.296	0.183	0.125	0.062	0.060	0.040	0.043	0.057	-0.030	0.050
9M	0.187	0.175	0.111	0.047	-0.004	0.032	0.002	-0.028	-0.013	0.048	0.064
12M	0.190	0.144	0.062	0.004	0.004	-0.014	-0.024	-0.051	-0.054	-0.023	0.058
24M	0.047	-0.166	-0.054	-0.057	-0.028	-0.003	-0.039	-0.045	-0.072	-0.094	-0.161
Bank Credit Gap											
3M	0.186	0.310	0.232	0.221	0.201	0.170	0.178	0.177	0.115	0.105	0.057
6M	0.277	0.266	0.231	0.186	0.173	0.106	0.154	0.174	0.097	0.086	0.034
9M	0.259	0.276	0.222	0.139	0.108	0.110	0.095	0.102	0.084	-0.005	0.075
12M	0.293	0.232	0.174	0.132	0.067	0.029	0.015	0.062	0.019	0.044	0.053
24M	0.391	0.273	0.107	0.139	0.124	0.083	0.030	0.116	0.149	0.155	0.163

Table A.2: GDP regressions, predictive R^2 gains versus AR(1) model (selected indicators)

τ	*0.05*	*0.1*	*0.2*	*0.3*	*0.4*	*0.5*	*0.6*	*0.7*	*0.8*	*0.9*	*0.95*
FCI											
3M	0.195	0.057	0.063	-0.033	0.003	-0.055	-0.069	-0.284	-0.306	-0.025	0.005
6M	-0.058	0.082	0.033	0.032	0.041	0.073	0.059	-0.159	-0.156	-0.194	-0.258
9M	0.240	0.199	0.134	0.245	0.177	0.029	0.023	-0.034	-0.174	-0.107	-0.127
12M	0.350	0.120	0.214	0.156	0.155	0.090	-0.051	-0.061	-0.136	-0.065	-0.067
24M	-0.694	-0.181	-0.096	0.043	0.020	-0.021	-0.058	-0.233	-0.142	-0.366	0.078
FCI bond											
3M	-0.010	-0.002	0.114	0.035	-0.008	-0.039	-0.023	-0.098	-0.057	0.072	-0.023
6M	0.124	0.072	0.064	-0.007	-0.018	0.007	0.014	0.014	-0.018	-0.142	-0.198
9M	0.155	0.160	0.077	0.153	0.068	-0.004	-0.013	-0.005	0.038	-0.197	-0.038
12M	0.143	0.098	0.161	0.141	0.084	0.045	0.006	-0.031	-0.014	-0.117	-0.101
24M	-0.307	-0.220	-0.102	0.101	0.122	0.105	0.019	-0.020	0.007	-0.133	0.009
CISS											
3M	0.262	0.136	0.026	0.055	-0.026	-0.063	-0.039	-0.128	-0.266	-0.643	-0.439
6M	0.266	0.322	0.064	0.042	0.005	-0.038	-0.065	-0.082	-0.080	-0.370	-0.142
9M	0.318	0.352	0.140	0.184	0.118	0.014	-0.095	-0.116	-0.274	-0.440	-0.788
12M	0.410	0.366	0.267	0.165	0.060	-0.046	-0.137	-0.097	-0.373	-0.186	-0.711
24M	-0.445	-0.151	0.036	0.142	0.108	0.058	-0.035	-0.052	-0.161	-0.369	-0.341
Credit Spread											
3M	0.130	-0.028	0.018	-0.018	0.004	-0.008	0.000	0.004	0.002	0.030	0.031
6M	0.107	0.008	-0.006	-0.003	0.014	0.059	0.028	-0.002	0.007	-0.030	0.140
9M	-0.028	-0.067	-0.023	0.003	0.030	0.023	0.021	-0.013	0.003	-0.043	-0.051
12M	-0.010	-0.108	0.007	0.012	0.013	0.002	0.002	-0.007	-0.022	-0.066	-0.004
24M	0.125	0.017	-0.011	-0.006	-0.004	-0.012	-0.003	-0.002	-0.012	-0.020	-0.087
VIX											
3M	0.255	0.060	0.061	0.041	0.024	-0.015	-0.047	-0.046	-0.017	-0.084	-0.103
6M	0.131	0.084	0.072	0.005	-0.038	-0.006	-0.025	-0.038	0.023	-0.046	0.125
9M	0.134	0.030	0.089	0.076	-0.023	-0.022	-0.035	-0.032	-0.022	-0.022	-0.020
12M	0.118	0.066	0.088	0.026	0.001	-0.015	-0.027	-0.032	-0.029	-0.026	0.010
24M	0.044	-0.180	-0.022	-0.029	-0.010	-0.001	0.001	-0.004	-0.029	-0.074	-0.188
Bank credit gap											
3M	0.015	0.095	-0.007	0.018	0.008	-0.021	-0.017	-0.011	0.005	-0.036	-0.110
6M	0.057	0.077	0.091	0.064	0.030	-0.011	-0.003	0.013	-0.003	-0.015	0.024
9M	0.086	0.108	0.154	0.053	0.005	-0.015	0.008	0.001	-0.045	-0.139	0.043
12M	0.201	0.157	0.163	0.084	0.034	-0.011	-0.008	-0.036	-0.070	0.014	0.051
24M	0.356	0.268	0.104	0.154	0.111	0.045	-0.053	-0.008	-0.012	-0.005	-0.046

Table A.3: IP regressions, predictive R^2 gains versus constant (selected indicators)

τ	*0.05*	*0.1*	*0.2*	*0.3*	*0.4*	*0.5*	*0.6*	*0.7*	*0.8*	*0.9*	*0.95*
FCI											
3M	0.370	0.186	0.121	0.089	0.044	-0.005	-0.022	-0.024	-0.002	-0.034	-0.155
6M	0.274	0.160	0.088	0.065	0.067	0.039	0.044	0.032	0.008	-0.089	-0.218
9M	0.266	0.113	0.044	0.033	0.050	0.049	0.042	0.038	0.027	0.009	-0.112
12M	0.256	0.120	0.095	0.082	0.061	0.055	0.059	0.063	0.075	0.089	0.032
24M	0.155	0.114	0.063	0.090	0.094	0.083	0.048	0.040	-0.003	0.017	-0.001
FCI bond											
3M	0.193	0.078	0.071	0.045	0.010	-0.019	-0.035	-0.030	-0.002	0.004	-0.055
6M	0.217	0.073	0.050	0.050	0.066	0.049	0.029	0.015	-0.007	-0.023	-0.009
9M	0.134	0.030	0.034	0.017	0.034	0.036	0.040	0.028	0.003	-0.003	0.017
12M	0.096	0.030	0.064	0.057	0.045	0.019	0.030	0.047	0.077	0.095	0.074
24M	0.203	0.148	0.049	0.088	0.093	0.091	0.067	0.037	0.013	0.030	0.042
CISS											
3M	0.466	0.284	0.162	0.079	0.024	-0.006	-0.053	-0.090	-0.099	-0.052	-0.092
6M	0.398	0.262	0.133	0.091	0.053	0.015	-0.011	-0.036	-0.034	-0.028	-0.103
9M	0.431	0.289	0.176	0.108	0.065	0.014	-0.038	-0.079	-0.091	-0.091	-0.114
12M	0.481	0.329	0.192	0.135	0.074	0.033	-0.007	-0.049	-0.037	-0.035	-0.104
24M	0.184	0.258	0.220	0.172	0.145	0.124	0.093	0.051	0.006	0.044	-0.064
Credit Spread											
3M	0.127	0.045	0.026	0.020	0.008	-0.006	-0.004	0.002	0.012	0.010	-0.035
6M	0.124	0.028	0.055	0.055	0.040	0.020	0.009	-0.006	-0.027	-0.059	-0.072
9M	0.079	0.005	-0.001	0.005	0.006	0.012	0.005	-0.022	-0.012	-0.007	0.004
12M	0.059	-0.025	-0.023	0.007	0.004	0.001	0.025	0.020	0.039	0.046	0.080
24M	0.323	0.171	-0.010	-0.026	-0.040	-0.035	-0.039	-0.044	-0.021	0.015	0.063
VIX											
3M	0.337	0.199	0.067	0.032	0.032	0.028	0.018	-0.004	-0.014	-0.031	-0.069
6M	0.195	0.142	0.075	0.073	0.058	0.030	0.006	-0.012	-0.054	-0.126	-0.132
9M	0.139	0.109	0.056	0.056	0.034	0.014	-0.005	-0.035	-0.048	-0.094	-0.097
12M	0.100	0.065	0.054	0.041	0.016	0.020	0.025	0.031	0.030	0.049	0.071
24M	0.146	0.004	-0.013	-0.016	-0.034	-0.025	-0.016	-0.025	-0.031	-0.015	0.064
Bank credit gap											
3M	0.112	0.041	0.011	0.008	0.002	-0.019	-0.006	-0.017	-0.048	-0.034	-0.090
6M	0.122	0.062	0.064	0.045	0.038	0.010	0.001	-0.029	-0.051	-0.067	-0.081
9M	0.052	0.039	0.033	0.008	0.006	-0.003	-0.016	-0.046	-0.038	0.013	0.075
12M	0.017	0.040	0.010	0.023	-0.001	-0.009	-0.007	0.017	0.051	0.062	0.108
24M	0.421	0.322	0.226	0.182	0.141	0.097	0.043	0.000	-0.003	-0.037	0.013

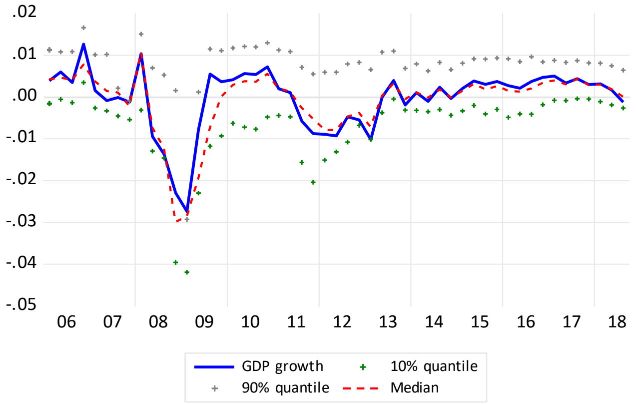
Table A.4: IP regressions, predictive R^2 gains versus AR(1) model (selected indicators)

τ	***0.05***	***0.1***	***0.2***	***0.3***	***0.4***	***0.5***	***0.6***	***0.7***	***0.8***	***0.9***	***0.95***
FCI											
3M	0.272	0.139	0.115	0.086	0.043	0.006	0.011	0.008	0.019	-0.007	-0.124
6M	0.188	0.137	0.061	0.020	0.036	0.037	0.034	0.043	0.034	-0.059	-0.235
9M	0.200	0.105	0.069	0.052	0.078	0.065	0.057	0.056	0.039	-0.002	-0.120
12M	0.247	0.171	0.123	0.106	0.074	0.071	0.069	0.045	0.010	-0.005	-0.056
24M	-0.092	-0.066	0.011	0.030	0.037	0.043	0.031	0.043	-0.046	-0.073	-0.200
FCI bond											
3M	0.067	0.025	0.064	0.041	0.008	-0.008	-0.002	0.002	0.019	0.029	-0.027
6M	0.124	0.048	0.022	0.005	0.035	0.047	0.020	0.026	0.020	0.005	-0.023
9M	0.055	0.022	0.059	0.036	0.063	0.053	0.055	0.046	0.015	-0.014	0.010
12M	0.086	0.086	0.093	0.081	0.059	0.036	0.040	0.029	0.012	0.001	-0.010
24M	-0.031	-0.026	-0.003	0.028	0.036	0.050	0.051	0.039	-0.029	-0.059	-0.148
CISS											
3M	0.414	0.231	0.160	0.076	0.027	0.001	-0.014	-0.070	-0.074	-0.028	-0.070
6M	0.272	0.246	0.104	0.048	0.024	0.012	-0.019	-0.023	-0.012	0.006	-0.140
9M	0.415	0.301	0.188	0.133	0.081	0.024	-0.024	-0.060	-0.079	-0.085	-0.130
12M	0.489	0.353	0.220	0.155	0.081	0.046	-0.001	-0.077	-0.109	-0.132	-0.197
24M	-0.068	0.073	0.161	0.116	0.085	0.080	0.062	0.036	-0.032	-0.063	-0.316
Credit Spread											
3M	0.014	-0.001	0.012	0.007	-0.002	-0.002	-0.004	0.009	0.025	0.016	-0.012
6M	0.005	-0.003	0.000	0.008	0.008	0.002	0.000	0.001	0.006	-0.022	-0.029
9M	0.058	-0.011	0.002	0.005	0.012	0.009	0.014	-0.004	-0.003	-0.035	-0.048
12M	0.067	0.005	0.007	0.020	0.012	0.014	0.016	-0.013	-0.030	-0.030	-0.058
24M	0.163	0.132	-0.046	-0.042	-0.040	-0.032	-0.024	-0.040	-0.034	0.015	0.048
VIX											
3M	0.251	0.161	0.054	0.020	0.022	0.031	0.018	0.003	-0.001	-0.024	-0.045
6M	0.085	0.116	0.022	0.027	0.026	0.013	-0.004	-0.005	-0.021	-0.087	-0.087
9M	0.120	0.094	0.059	0.056	0.039	0.011	0.005	-0.016	-0.039	-0.124	-0.154
12M	0.108	0.091	0.082	0.054	0.023	0.033	0.015	-0.001	-0.040	-0.026	-0.069
24M	-0.054	-0.043	-0.049	-0.032	-0.034	-0.022	-0.002	-0.022	-0.044	-0.014	0.050
Aa											
3M	-0.010	-0.004	-0.003	-0.009	-0.005	-0.012	-0.005	-0.009	-0.034	-0.028	-0.075
6M	0.043	0.039	0.011	-0.002	0.006	-0.007	-0.007	-0.019	-0.015	-0.031	-0.031
9M	0.035	0.036	0.038	0.013	0.008	-0.005	-0.007	-0.020	-0.027	-0.011	0.028
12M	0.027	0.068	0.044	0.038	0.007	0.008	-0.015	-0.019	-0.020	-0.015	-0.033
24M	0.285	0.290	0.199	0.169	0.142	0.099	0.057	0.003	-0.016	-0.036	-0.003

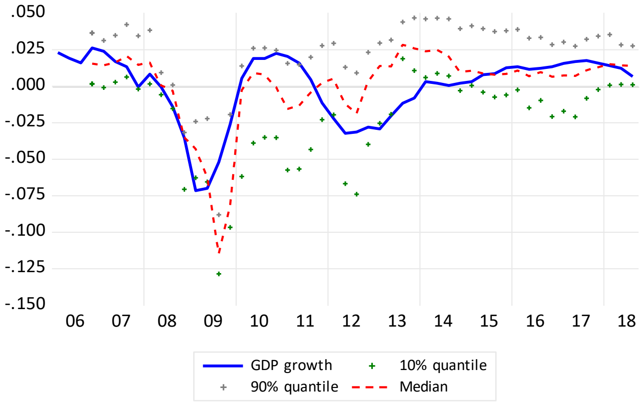
Annex B: 12-month ahead forecasts based on CISS

Figure B1: Out-of-sample forecasts

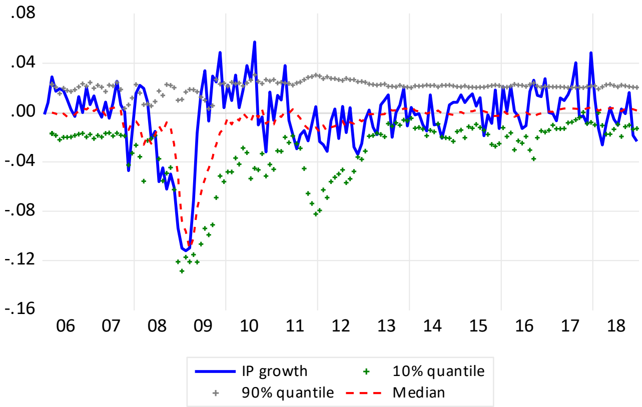
(i) GDP, 3-month horizon



(ii) GDP, 12-month horizon



(iii) IP, 3-month horizon



(iv) IP, 12-month horizon

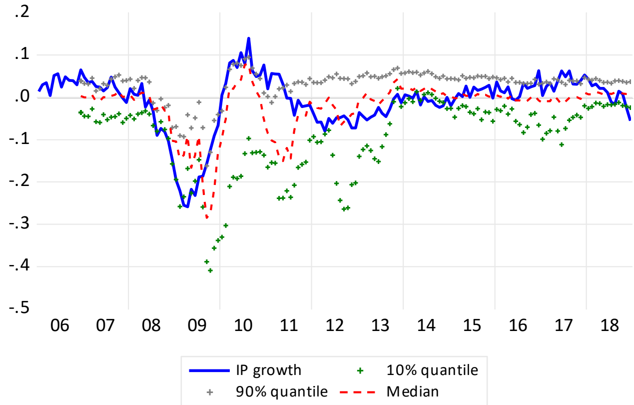


Figure B2: Recession probabilities

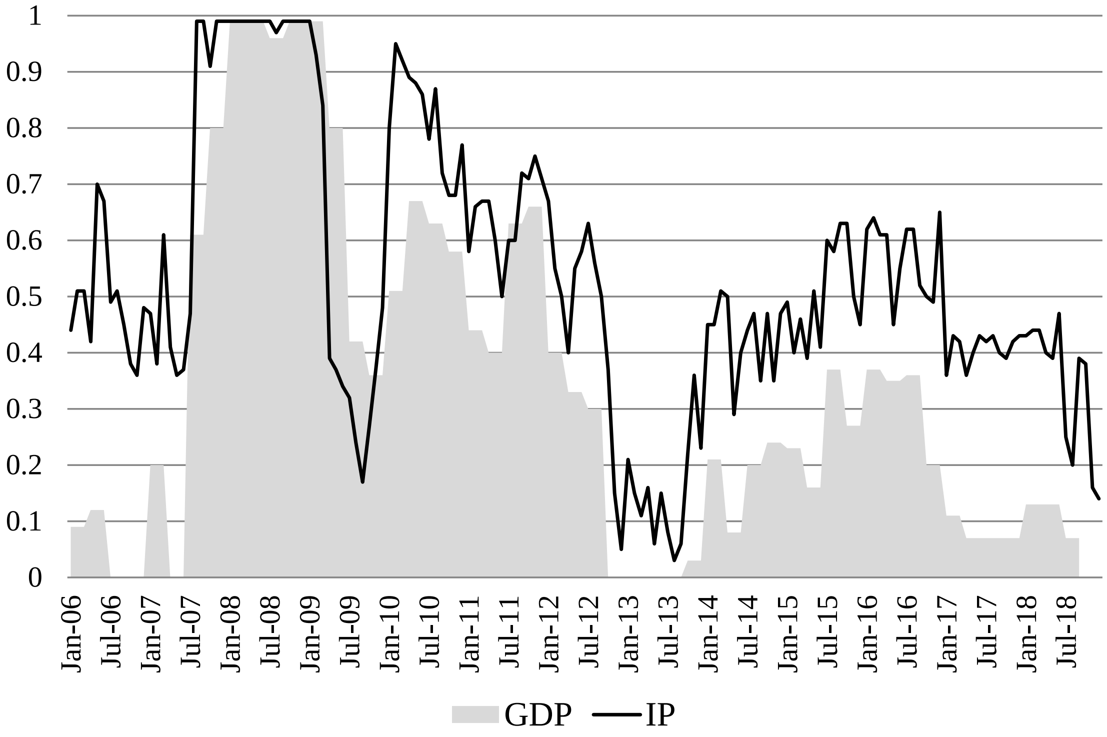
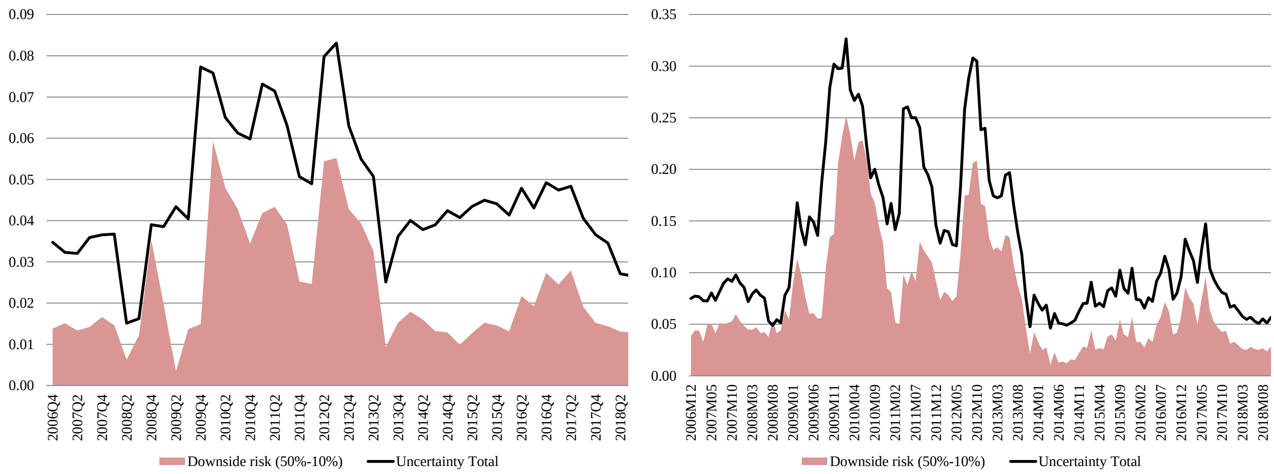


Figure B3: Uncertainty measures

(a) GDP (b) IP



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