



Notes on Financial Stability and Supervision

No. 24
March 2021

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Notes on Financial Stability
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Growth-at-risk in Italy during the covid-19 pandemic

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Overview

This note investigates whether financial markets can help in predicting extreme macroeconomic outcomes associated with very rare events using the first outbreak of the COVID-19 pandemic in Italy as a case study. The ‘growth-at-risk’ (GAR) models we examine miss the economic contraction the country experienced in the first half of 2020. The reason is that the financial markets moved too late to have an impact on the forecasts, even at relatively short horizons. Our results suggest that, while GaR models provide a useful description of historical tail dynamics for economic activity, their forecasts should not be taken at face value and directly employed to calibrate pre-emptive policy actions.

Introduction and main conclusions

Using post-war data on the US economy, Adrian et al. (2019, 2020) find that financial indicators provide useful and timely information on the probability of observing a recession over medium-term horizons.¹ Following their analysis, a number of institutions introduced ‘GDP-at-risk’ (GaR) models into their risk assessment frameworks in order to capture the dynamic relation between financial markets and the real economy in a flexible way, allowing for stronger correlations to emerge in ‘bad times’.

¹ Adrian T., N. Boyarchenko and D. Giannone (2019), ‘Vulnerable growth’, *American Economic Review*, 109(4), 1263-89. Adrian T., P. Adams, N. Boyarchenko and D. Giannone (2020), ‘Forecasting macroeconomic risks’, Centre for Economic Policy Research Discussion Paper 14436.

The debate on the merits and limitations of this approach remains open. The evidence for Italy is mixed at best: the left tail of the output distribution fluctuates significantly over time in relation *inter alia* to credit conditions, trade flows and economic uncertainty, but these regularities cannot be reliably exploited for out-of-sample forecasting (Alessandri et al., 2019; Busetti et al., 2020).²

This note investigates whether financial markets can help in predicting extreme macroeconomic outcomes associated with very rare events using the outbreak of the COVID-19 pandemic in Italy as a case study. We re-estimate the quantile GaR regressions in Alessandri et al. (2019) and study their forecasts for GDP, industrial production ('IP') and Ita-coin (Aprigliano and Bencivelli, 2013) around the spring and summer of 2020, using as predictor a synthetic 'financial condition index' (FCI) for the Italian economy (Miglietta and Venditti, 2019).³ The COVID-19 shock is admittedly a difficult test for any forecasting model given that the outbreak of the pandemic and its widespread economic impact probably rank among the least predictable events in recent decades. However, GaR models are in principle designed to cope exactly with 'tail' scenarios. Furthermore, given the early experience of COVID-19 in China at the end of 2019, it should have been possible for financial markets to quantify and price the risk of an economic recession better than could firms and households, which (both in Europe and in the USA) largely ignored the pandemic until dramatic lockdown measures were introduced in the early months of 2020.

The result of the (performance) test for the GaR approach in this case is negative; indeed, the models we examine miss the economic contraction experienced in Italy in the first half of 2020. The reason is that the financial markets moved too late to have an impact on the forecasts, even at relatively short horizons. The FCI only rose in March, when lockdown measures were actually introduced by the Italian Government. This has likely hindered the models' capacity to anticipate the impending slowdown. The 10% tail predictions for GDP growth in Q2-2020 based on the data up to March are virtually flat. The same is true for industrial production, despite the informational gain stemming from the monthly frequency and the availability of additional observations for April and May. The model based on Ita-coin predicts an increase in the likelihood of an economic contraction over the summer, but the prediction turns out to be mechanically driven by a combination of (i) the decline observed in April and May and (ii) the strong autoregressive behaviour of Ita-coin in the left tail of its distribution.

Taken together, the results suggest that GaR models provide a useful description of historical tail dynamics for economic activity, but their forecasts must be scrutinized carefully and should not be taken at face value and directly employed to calibrate pre-emptive policy actions.

² Alessandri P., L. Del Vecchio and A. Miglietta (2019), 'Financial conditions and growth-at-risk in Italy', Banca d'Italia, Temi di Discussione (Working Papers), 1242. Busetti, F., M. Caivano, D. Delle Monache and C. Pacella (2020), 'The time-varying risk of Italian GDP', Banca d'Italia, Temi di Discussione (Working Papers), 1288.

³ Aprigliano V. and L. Bencivelli (2019), 'Ita-coin: a new coincident indicator for the Italian economy', Banca d'Italia, Temi di Discussione (Working Papers), 935. Miglietta, A. and F. Venditti (2019), 'An indicator of macro-financial stress for Italy', Banca d'Italia, Quaderni di Economia e Finanza (Occasional Papers), 497.

1. Empirical framework

The design of the quantile regressions mimics closely that of Adrian et al. (2019) and is described in detail in Alessandri et al. (2019). The regressions have the following form:

$$\Delta EA_{t,t+h} = c + \gamma \Delta EA_{t-h,t} + \beta FCI_t + \varepsilon_t, \quad (1)$$

where EA denotes an economic activity indicator (alternatively GDP growth, IP growth or Ita-coin), FCI is the financial condition index constructed by Miglietta and Venditti (2019), which summarizes a large set of bank and market-based financial indicators for Italy, and the forecasting horizon h varies between 3 and 12 months. The regression captures the relation between the current level of FCI and the future performance of the economy, controlling for the latest observed value of the economic activity indicator of interest. We estimate it separately around three percentiles of the distribution, $\tau = (10, 50, 90)$, focusing on the performance of the 10th percentile in tracking the data before and after the outbreak of the pandemic.⁴ Our objective is to test the usefulness of the GaR approach in real time, when forecasters typically have access to a host of conceptually similar series that are published at different times and can generate different predictions. We thus include in the estimation sample the observations that were actually available in July 2020, when the tensions in financial markets had essentially subsided. The models are consequently estimated using a ‘ragged’ dataset where the first observation is January 1998, when the FCI series begins, and the last observation changes across regressions based on the availability of the target variable. This implies that the forecasts for GDP, IP and Ita-coin are based respectively on samples ending in March, May and June 2020.

2. Results

2.1 Overview

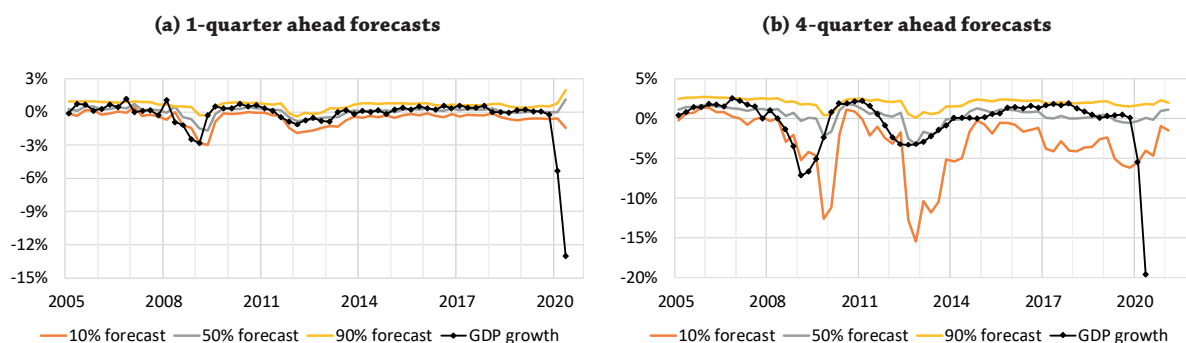
Figures 1, 2 and 3 show the quantile forecasts obtained respectively for GDP growth, IP growth and Ita-coin. For each indicator we report forecasts at horizons of 3 months (left-hand panels) and 12 months (right-hand panels).⁵ The drop in GDP growth recorded in Q1-2020 and Q2-2020 falls well below the corresponding 10% quantile forecast (see panel (a) in Figure 1). This is partly true also for the 4-quarter ahead forecast (see panel (b) in Figure 1).⁶ In this case, the model anticipates a widening of the distribution and a decline in the left tail starting from the end of 2019, implying that the March observation is roughly in line with the 10% prediction. However, the observation for June is well outside the forecast range. Furthermore, the annual growth rate of GDP is more volatile and its forecasts fluctuate widely over the sample period, particularly in the critical phases of 2009 and 2012-13. Overall, the increase in downside risk registered by the model between 2019 and 2020 is not particularly significant by historical standards.

⁴ The first percentile is used as an alternative in some of the robustness tests.

⁵ The timing convention in the figures is the standard one: for every month or quarter t and horizon h , the data represents output growth up to t (calculated over the previous h periods) and the forecasts show the associated predictions (computed with the data available at time t).

⁶ Notice that the quarterly and annual growth rates shown in panels (a) and (b) of Figure 1 are similar because the quarterly growth of GDP was close to zero throughout 2019 (see panel (a) in Figure 1).

Figure 1 – Quantile forecasts for GDP growth (1)

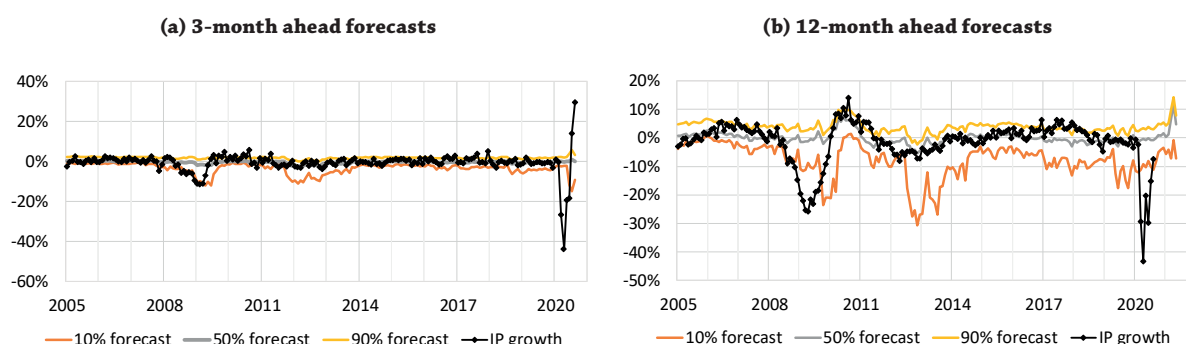


(1) The data is displayed until Q2-2020; the last observation used to compute the forecasts is Q1-2020.

In principle, monthly data could have a better chance of capturing the COVID-19 shock. In practice, that was not the case. The observations for IP growth between March and June lie well below the corresponding 10% forecasts, both at the 3-month and 12-month horizon (Figure 2). It is interesting to note, however, that the 3-month forecasts capture to some extent the increase in uncertainty caused by the pandemic; after March the quantiles widen, suggesting at once an increase in downside risks and a higher likelihood of observing positive growth rates (see panel (a) in Figure 2).⁷ This prediction turns out to be qualitatively consistent with the high volatility of IP over the spring and summer of 2020. However, the range of the forecasts is too narrow: the negative values of May and June are again below the 10% forecasts, while the rebound observed in July and August (which was in itself abnormal by historical standards) moved the indicator above the 90% forecasts.

Ita-coin presents a somewhat different picture. The regressions miss the drop in April and May in this case too (Figure 3), but the 3-month ahead forecast unambiguously signals that the situation will deteriorate further in the short run (see panel (a) in

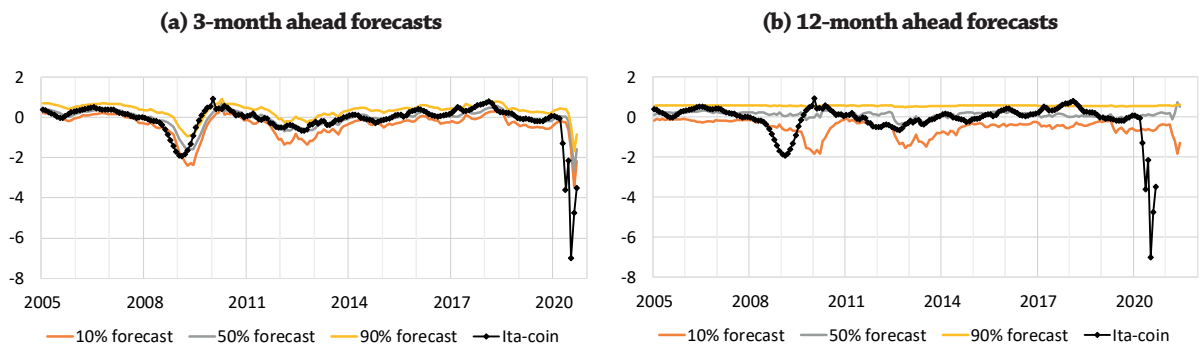
Figure 2 – Quantile forecasts for industrial production growth (1)



(1) The data is displayed until August 2020; the last observation used to compute the forecasts is May 2020.

⁷ Alessandri et al. (2019) find that recessions are often anticipated by an increase in ‘uncertainty’, defined as the distance between the top and bottom quantiles of the predictive distribution.

Figure 3 – Quantile forecasts for Ita-coin (1)



(1) The data is displayed until August 2020; the last observation used to compute the forecasts is June 2020.

Figure 3).⁸ As we show below, however, the difference between Ita-coin and IP reflects the autocorrelation structure of the two variables rather than their relationship with the financial conditions subsumed in the FCI (see Section 2.3).⁹

2.2 A closer look at the monthly projections

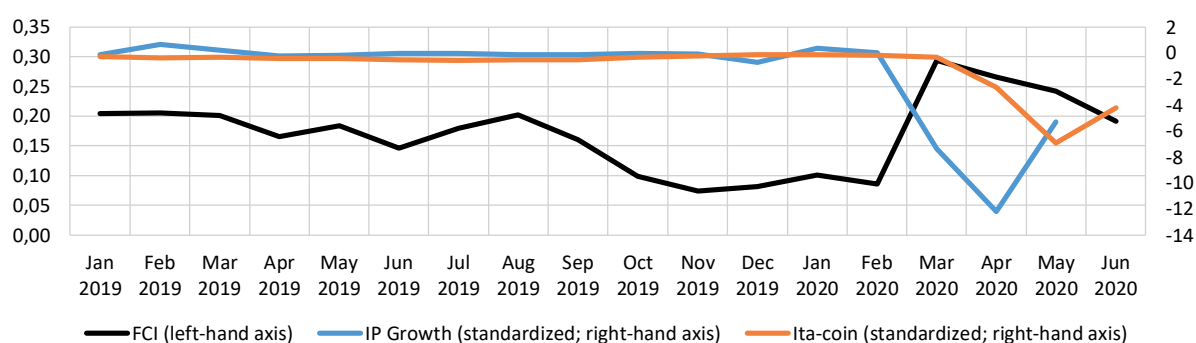
The monthly projections in Figures 2 and 3 raise an obvious question: why does the market reaction to the COVID-19 crisis fail to show up in the forecasts? The main reason is that the FCI – like most indicators of financial market distress – peaked in the spring of 2020, almost at the same time as economic activity ground to a halt. To illustrate this point, in Figure 4 we compare the dynamics of FCI, IP and Ita-coin between the end of 2019 and the summer of 2020. The IP and Ita-coin series are standardized to improve readability and we only include the observations that are actually exploited within the regressions, omitting those that were not available in July. The chart shows that FCI declined steadily from the summer of 2019 and that this trend was reversed only in March 2020, the month in which drastic lockdown measures were introduced across the country. Industrial production contracted sharply in March and reached its trough in April and the implied time lag is clearly too short to be exploited in the regressions. The situation is similar for Ita-coin, whose decline was more gradual and initially smaller in relative terms, with fluctuations between April and May of the order of about 7 standard deviations instead of 12.¹⁰ This difference may reflect the broader nature of the Ita-coin indicator, which captures for instance various services that were less affected than (some) manufacturing industries. However, the gap between peak and trough is again of two months only, so the FCI misses the ‘tail outcome’ in this

⁸ The Ita-coin outlook is actually negative at the 12-month horizon too; the 90% forecast is constant whereas the 10% drops to an all-time minimum of -1.9, pointing to a sharp increase in downside risks in 2021 (see panel (b) in Figure 3). This conclusion is somewhat weakened by a puzzling increase of the median forecast.

⁹ The 90% forecast for Ita-coin is virtually constant over time because both the AR(1) and the FCI coefficients in that regression are very close to zero. This also causes the forecasts to cross each other in the out-of-sample projections: in particular, the median forecast temporarily exceeds the 90% forecast in 2021.

¹⁰ Notice that Ita-coin reached its trough in July whereas IP bounced back after the spring, with high positive monthly growth rates from June onwards (see Figures 2 and 3).

Figure 4 – Financial conditions and economic activity around March 2020 (1)



(1) Financial condition index and standardized industrial production and Ita-coin. Industrial production and Ita-coin are shown, respectively, as a quarterly growth rate and as a level. The industrial production and Ita-coin series are truncated at the last observation used for the estimation, i.e. respectively May and June 2020.

case too. Actually, the February observation for FCI, which should predict the Ita-coin outcome for May, is below 0.10, a historically low level.

2.3 Industrial production versus Ita-coin

An important point is that the discrepancy between IP and Ita-coin emerging in Figures 2 and 3 has nothing to do with the relation between these variables and the FCI. The discrepancy depends exclusively on a combination of (i) the ‘informational advantage’ of the Ita-coin regression, which uses data up to June instead of May, and (ii) the greater persistence of Ita-coin, particularly in the left tail of the distribution. To illustrate these issues we report in Table 1 the quantile regressions estimated using the standardized IP and Ita-coin series displayed in Figure 4 and a common sample ending in May 2020 (note that the standardization is necessary to make the regression coefficients comparable across models). For each indicator the table shows the regression estimated in the tail ($\tau=10$) and at the median ($\tau=50$). Two facts stand out. First, the median FCI

Table 1 – Quantile regressions based on standardized industrial production and Ita-coin series (1)

(a) industrial production growth									
50 th quantile					10 th quantile				
Variable	Coeff.	SE	t-Stat.	Prob.	Variable	Coeff.	SE	t-Stat.	Prob.
C	0.268	0.064	4.19	0.000	C	-0.002	0.143	-0.02	0.988
FCI	-1.430	0.345	-4.15	0.000	FCI	-4.807	1.501	-3.20	0.002
IP lag	-0.047	0.108	-0.43	0.665	IP lag	0.214	0.240	0.89	0.373

(b) Ita-coin									
50 th quantile					10 th quantile				
Variable	Coeff.	SE	t-Stat.	Prob.	Variable	Coeff.	SE	t-Stat.	Prob.
C	0.123	0.053	2.32	0.021	C	-0.322	0.087	-3.73	0.000
FCI	-1.502	0.369	-4.08	0.000	FCI	-1.286	0.900	-1.43	0.154
Ita-coin lag	0.712	0.060	11.83	0.000	Ita-coin lag	0.863	0.117	7.35	0.000

(1) The table shows estimates of the quantile regression for Ita-coin (see panel (b) above) and the quarterly growth rate of Industrial Production (see panel (a) above). The data is standardized to make the regression coefficients comparable. The sample covers the period between January 1998 and May 2020.

coefficients of the two indicators are similar, while the tail coefficient is larger for IP. Hence, the difference across forecasts is not caused by a higher sensitivity of Ita-coin to FCI. Second, Ita-coin is highly persistent (both at the median and in the tail) whereas IP growth is not. These results suggest that the difference may come from the latest observations: the Ita-coin regression runs with data up to June, so it ‘sees’ the initial drop and, due to the large AR(1) coefficient, this drop is used to predict future values. This does not happen in the IP regression, where the last value is May and the AR(1) coefficient is almost zero.

To corroborate this interpretation, in Figure A1 of the Annex we show the out-of-sample predictions for the standardized IP and Ita-coin series using alternatively December 2019, March 2020 and May or June 2020 as sample endpoints (see the three panels respectively). In the first two cases the regressions are put on an equal footing, while in the third we use the extra observation available for Ita-coin. The forecasts for March are virtually identical and equally distant from the actual outcomes. Those for June are again very similar; in fact, in this case IP is predicted to drop slightly more owing to its larger FCI coefficient. It is only for July-August that the models predict a steeper decline for Ita-coin. The reason is clearly that the model sees the trough and rebound of May-June and projects it forward using its large AR(1) coefficient.

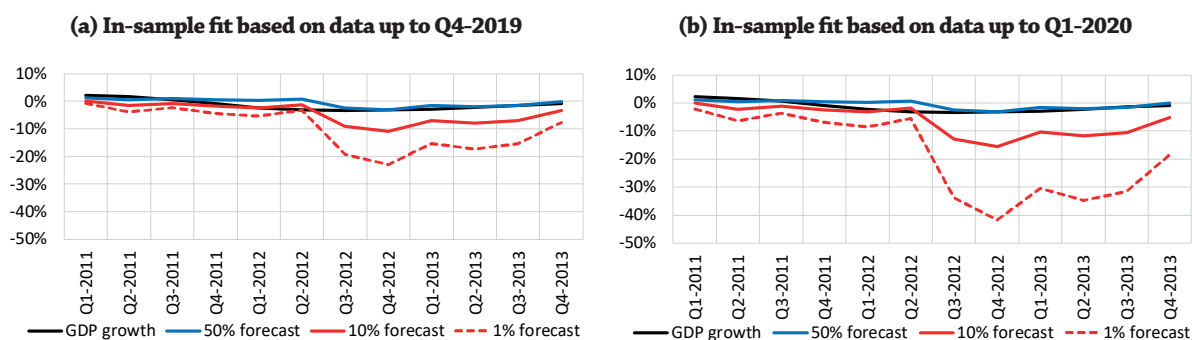
2.4 An analysis of extreme (1%) tail risks

The COVID-19 crisis was arguably a ‘rare disaster’ with an *ex ante* probability far below 10%. However, the quality of the predictions remains roughly unchanged if the regressions are estimated around lower percentiles of the distributions. In Figure A2 of the Annex we replicate the analysis above but estimate the regressions for the 1st rather than the 10th percentile of the data. The forecasts are by construction lower in terms of levels, with starting values of around –2 standard deviations for both indicators at the beginning of the year. However, as in the previous case, they are more or less constant over the spring and they only drop when the first negative data points enter the estimation sample. Irrespective of the percentile, the models need to see an incipient slowdown in the data in order to generate a more pessimistic picture of the economic outlook.¹¹

The regressions around the first percentile are interesting from another perspective. The data points corresponding to the spring of 2020 redefine the left tail of the distributions of the three economic activity indicators: contractions of the order of 8 to 12 standard deviations demonstrate that the data is far more volatile than one would have expected. In the models, this leads to an upward revision of the *likelihood* of all the recessionary episodes that took place earlier in history. To illustrate this point, in Figure 5 we report two sets of in-sample forecasts for 2012 based on datasets

¹¹ Figure A2 shows that the 1% regressions fit almost perfectly the first negative outcomes of IP and Ita-coin as soon as these enter the estimation sample, i.e. respectively in March (panel (b) above) and June (panel (c) above). This does not happen for the 10% regressions displayed in Figure A1. In the tails, a few observations can have a large impact on the quantile of interest; if the observations are sufficiently far from the rest of the sample, the loss function used in quantile regressions will give them a weight close to one, generating a residual close to zero.

Figure 5 – Reassessing the 2012 recession on the basis of the 2020 experience (1)



(1) The charts show data and fitted value for GDP growth from quantile regressions estimated around the 50th, 10th and 1st percentiles of the distribution. In panel (a) the data runs until Q4-2019. In panel (b) it runs until Q1-2020, thus including the first sharp drop in GDP caused by the COVID-19 crisis.

ending alternatively in Q4-2019 (panel a) and in Q1-2020 (panel b). The regressions initially assign a likelihood of about 1% to the GDP growth outcome for Q2-2012. This call is made as soon as the observation enters the dataset, and it is not significantly revised between 2012 and 2019. The occurrence of a large shock in Q1-2020, however, has interesting implications for these results. The 50% and 10% projections are virtually unchanged but the 1% projections, which are redefined to take into account the COVID-19 shock, shift downwards, with minima that move from -20 to -40 percentage points. As a result, in retrospect the 2012 recession looks like a 10% rather than a 1% probability event.

Annex

Figure A1 – 3-month-ahead 10% forecasts based on alternative sample endpoints
(standardized industrial production and Ita-coin series)

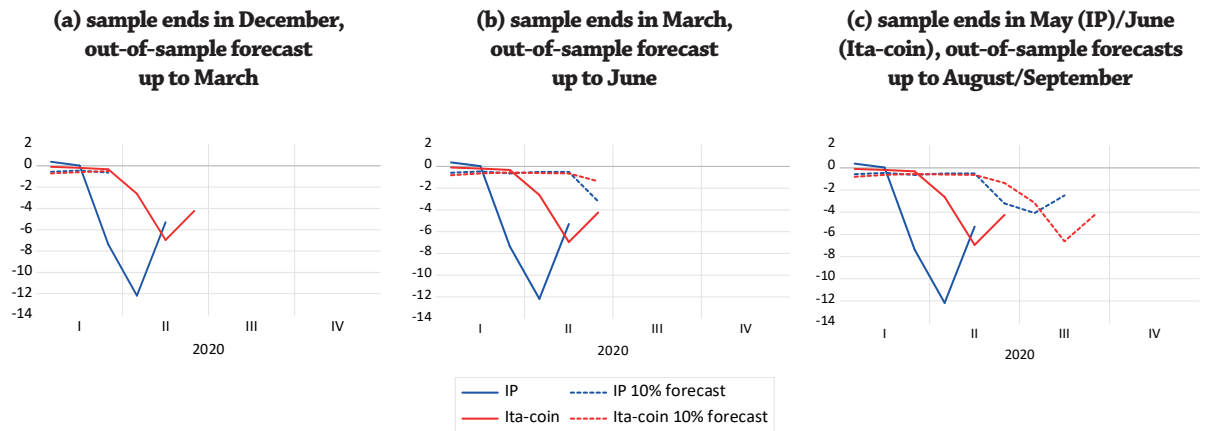


Figure A2 – 3-month-ahead 1% forecasts based on alternative sample endpoints
(standardized industrial production and Ita-coin series)

