Forecasting the Covid-19 recession and recovery: Lessons from the financial crisis

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ABSTRACT

We consider simple methods to improve the growth nowcasts and forecasts obtained by mixed-frequency MIDAS and UMIDAS models with a variety of indicators during the Covid-19 crisis and recovery period, such as combining forecasts across various specifications for the same model and/or across different models, extending the model specification by adding MA terms, enhancing the estimation method by taking a similarity approach, and adjusting the forecasts to put them back on track using a specific form of intercept correction. Among these methods, adjusting the original nowcasts and forecasts by an amount similar to the nowcast and forecast errors made during the financial crisis and subsequent recovery seems to produce the best results for the US, notwithstanding the different source and characteristics of the financial crisis. In particular, the adjusted growth nowcasts for 2020Q1 get closer to the actual value, and the adjusted forecasts based on alternative indicators become much more similar, all unfortunately indicating a much slower recovery than without adjustment, and very persistent negative effects on trend growth. Similar findings also emerge for forecasts by institutions, for survey forecasts, and for the other G7 countries.

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1. Introduction

Nowcasting and short-term forecasting of economic conditions during the Covid-19 crisis are of key interest for economic and policy decision-making. Yet, unfortunately, obtaining reliable nowcasts and forecasts during crisis periods is very difficult, and all the peculiar features of the Covid-19 crisis make it even more difficult. Even sophisticated econometric approaches, such as mixed-frequency Bayesian VARs with stochastic volatility and quantile regressions combined with careful variable selection, have problems correctly predicting the depth of past US recessions and, in particular, the Covid-19 recession;

see for example (Carriero et al., 2020) and Plagborg-Møller et al. (2020), or (An & Loungani, 2020) for an analysis of the past performance of consensus forecasts.

Given this evidence, the goal of this paper is to consider simple methods that can improve nowcasts and forecasts specifically during the Covid-19 crisis and recovery period. We consider various approaches previously suggested in the literature, trying to adapt them when possible to the specificity of the Covid-19 period, and assessing their performance during the worst recent crisis, i.e., the financial crisis of 2007–09 and the subsequent recovery period. Specifically, we evaluate combining forecasts across various specifications for the same model and/or across different models (e.g., Timmermann (2006)), extending the model specification by adding MA terms (e.g., Foroni et al. (2019)), enhancing the estimation method by taking a similarity approach (e.g., Dendramis et al. (2020)), and adjusting the forecasts to put them

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back on track using a specific form of intercept correction (e.g., Clements and Hendry (1999)). Of course, all these methods are second best with respect to a sophisticated nonlinear/time-varying model capable of capturing the specificities of all the past recessions and of the Covid-19 recession. But the specification of such a model would be very complex, and its estimation would be limited by the rather short time series available for economic variables; see e.g. Ferrara et al. (2015) in the context of forecasting during the financial crisis. Hence, our second-best approach seems promising, though its usefulness and reliability has to be carefully assessed.

In terms of nowcasting models, we consider standard and unrestricted MIDAS specifications (see e.g. Clements and Galvão (2008), Foroni et al. (2015) and Ghysels et al. (2004)) for quarterly GDP growth, with commonly used monthly indicators (industrial production, employment, surveys, spreads, uncertainty measures, etc.), direct forecasting when the forecast horizon is larger than one quarter (e.g., Marcellino et al. (2006)), and a representative timing. For Covid-19 specifically, the timing of the exercise is the following. We nowcast the first quarter of 2020, and then forecast until the fourth quarter of 2022, given the monthly information available at the end of April 2020, before the first official release of US GDP for 2020Q1. At that point in time, we observe 2019Q4 for the GDP, and the first three months of 2020 for all of the monthly indicators we use. Hence, we nowcast the current quarter with monthly predictors available for all three months. This is important in the case of the Covid-19 pandemic, since the shutdown of the economy only started in March. For instance, industrial production monthly growth rates for the first three months of 2020 are -0.49, 0.46, and -5.55, respectively. Thus, nowcasting without the third month has limited information about the overall economic situation in the first quarter, since the imposed downturn was immediate and brutal.[1] Yet, even when information up to March 2020 is included within the best mixed-frequency models for nowcasting GDP growth in the first quarter of 2020, the resulting error is large (the nowcasts are too optimistic), in line with Carriero et al. (2020) and Plagborg-Møller et al. (2020). This suggests that the forecasted fast recovery could also not take place (as it also happened after the financial crisis). All of this justifies the need for nowcast and forecast improvement.

Among all of the methods considered to increase the reliability of nowcasts and forecasts for US growth for the Covid-19 period, adjusting them by an amount similar to the nowcast and forecast errors made during the financial crisis and subsequent recovery seems to produce the best results, notwithstanding the different source of the financial crisis and the fact that the services sector was less affected than in the Covid-19 case. In particular, the adjusted nowcasts for 2020Q1 produced by several mixed-frequency models get closer to the actual value,

and the adjusted forecasts based on alternative indicators become much more similar, all unfortunately indicating a much slower recovery and very persistent negative effects on trend growth. A similar finding emerges when considering original and adjusted nowcasts by the New York FED, and nowcasts and forecasts in the Survey of Professional Forecasters. (Schorfheide & Song, 2020) also obtain a quite pessimistic outlook for the current year using a mixed-frequency VAR model. Moreover, the results are in line with (Chang et al., 2020), who find, through the lens of impulse response analysis built on several historical health crises, that the output is still below the pre-shock level for as much as five years later.

The rationale to build our forecast adjustments for the Covid-19 crisis on the Great Recession lies in the similarities between the two downturns. Although the Great Recession and the Covid-19 crisis are due to different shocks, they also share similarities. First, uncertainty increased in both episodes, implying negative and long-lasting effects on real activity. Second, in terms of the size of the implied demand and supply shocks, the Great Recession is the most similar event to the Covid-19 crisis in the past decades. Hence, we believe that the performance of nowcasting models during the Great Recession could be informative for the Covid-19 crisis, which is indeed what we find empirically, at least for 2020Q1.

A similar finding also emerges when we replicate the analysis for the other G7 countries, with a similar timing. Moreover, the drop in GDP growth in 2020Q1 is expected to be particularly severe in France, Italy, and the UK, limited in Japan, and intermediate in Germany. Cross-country heterogeneity is also evident in the forecasts, with the first group of countries experiencing a very slow recovery and Japan a stronger recovery. These results seem in line with the extent of the spread of the disease and the differential policy responses in the countries under analysis.

Finally, as business cycle fluctuations are typically driven by those in private investment, we assess normal and adjusted Covid-19 nowcasts and forecasts for the US real private nonresidential fixed investment (PNFI), using the same models, indicators, and adjustment methods as for GDP growth. All models predict an important decrease in US investment growth in the first quarter of 2020. The most reliable indicator turns out to be industrial production (IP), with the average nowcast for 2020Q1 based on IP corresponding almost exactly to the actual observed decrease of -8.2%. The intercept adjustment returns a similarly precise nowcast, but more negative forecasts, as for the case of GDP growth.

The paper is structured as follows. Section 2 discusses the forecasting models with mixed-frequency data. Section 3 provides an overview of methods for forecast improvement during crises. Section 4 evaluates the performance of the models during the Covid-19 crisis in the US. Section 5 considers forecasts and errors for the financial crisis periods and uses that information to modify the US nowcasts and forecasts for the Covid-19 crisis and recovery, with some elaboration on their rationale. Section 6 repeats the whole analysis for US private investment, a key driver of business cycle fluctuations. Section 7 summarizes the main results and concludes. Additional empirical results, including those for the other G7 countries, are reported in Appendix.

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[1] Carriero et al. (2020) conducted a real-time evaluation with weekly updates of the nowcasts and likewise found that substantial changes in the nowcasts for 2020Q1 take place when information about March starts being used.

2. Forecasting models with mixed-frequency data

Let us define $t = 1, \ldots, T$ as the low-frequency (LF) time unit and $t_m = 1, \ldots, T_m$ as the high-frequency (HF) time unit. The HF time unit is observed m times in the LF time unit. Here, LF is quarterly and HF is monthly; hence $m = 3$. In addition, L indicates the lag operator at t_m frequency, while L^m is the lag operator at t frequency. Let us then define y_t as the stationary low-frequency target variable and x_t as the high-frequency stationary exogenous predictor, so that x is observable for every period t_m, while y is observable only every m periods. Using this notation, the models take the following general form:

$$y_{t_m} = \rho(L^m)y_{t_m-h_m} + \delta(L)x_{t_m-h_m} + u_{t_m} + \gamma(L^m)u_{t_m-h_m}, \quad (1)$$

where $t_m = m, 2m, \ldots, T_m$, h_m is the forecast horizon (we use the direct forecasting approach), and the error term u_{t_m} is white noise with $E(u_{t_m}) = 0$ and $E(u_{t_m}u'_{t_m}) = \sigma_u^2 < \infty$. Eq. (1) represents the UMIDAS-ARMA model proposed in Foroni et al. (2019). If the MA component is excluded, $\gamma(L^m) = 0$, the model (1) becomes a UMIDAS-AR model. If, in addition, the AR term is ignored, $\rho(L^m) = 0$, we get the UMIDAS specification. UMIDAS and UMIDAS-AR models (i.e., models without the MA component) are estimated by ordinary least squares (OLS), while the UMIDAS-ARMA model is estimated by nonlinear least squares (NLS) and also by generalized least squares (GLS), with details provided in Foroni et al. (2019).

The restricted version of (1), MIDAS-ARMA, is obtained by imposing a particular structure on the distributed lag polynomial $\delta(L)$:

$$y_{t_m} = \tilde{c}(L^m)y_{t_m-h_m} + \beta B(L, \theta)x_{t_m-h_m+w} + u_{t_m} + \gamma(L^m)u_{t_m-h_m}, \quad (2)$$

where

$$B(L, \theta) = \sum_{j=0}^{K} b(j, \theta)L^j,$$

$$b(j, \theta) = \frac{exp(\theta_1 j + \theta_2 j^2)}{\sum_{j=0}^{K} exp(\theta_1 j + \theta_2 j^2)},$$

and K is the maximum number of lags included of the explanatory variable.[2] In this application, $K = 12$ unless otherwise stated. Again, imposing $\gamma(L^m) = 0$ gives MIDAS-AR and if, in addition, $\tilde{c}(L^m) = 0$, the model reduces to MIDAS (Ghysels et al., 2006). All MIDAS models are estimated by NLS. Table 1 summarizes all the nowcasting and forecasting models under evaluation.[3]

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[2] The MIDAS-ARMA model in Eq. (2) includes only one explanatory variable x. While multiple indicators are possible from a theoretical point of view, in the MIDAS literature, single indicator models are typically used to simplify the estimation, and the resulting forecasts are then combined to take into consideration the entire information set. We also follow this approach in the UMIDAS context for comparability.

[3] We closely follow (Foroni et al., 2019) for the choice of hyperparameters in those models. We allow for 12 lags of the monthly predictor in all models, except in (u)midas-arma-K2 where it is set to 3, while the MA part is of order 1.

3. Forecast improvements during crises

It is well known that, unfortunately, the reliability of forecasts from econometric models decreases during crises and also during steep recoveries. There are various reasons for this pattern. First, econometric models are generally meant to capture the average behavior of the variables, while deep crises and steep recoveries are tail events. Specific models can be used to focus on the tail behavior, such as quantile regressions, but their performance with macro-data seems unsatisfactory due to the limited information available; see e.g. Carriero et al. (2020) and Plagborg-Møller et al. (2020). Second, the relationships among economic variables and the effects of economic policy can be different during crises, and this translates into changes in the model parameters. If a constant parameter model is used, as is common in the nowcasting literature, its performance will deteriorate, and particularly so when the parameters change most, i.e., during crises. A variety of time-varying parameter models have been proposed to address this issue; see for example the short review in Dendramis et al. (2020). Yet, their forecasting performance often remains unsatisfactory, as timing and estimating the size of the parameter changes would require a large amount of information in the form of many changes of similar magnitude. Third, even in the presence of constant parameters, the size of the shocks hitting the economy increases during crises (and often also changes during normal times). This suggests allowing for time-varying variances (and possibly covariances) of the model errors, for example with a stochastic volatility specification. Indeed, this can improve (in particular density) forecasts and nowcasts; see e.g. Carriero et al. (2015) and Clark (2011). Yet, this is in general insufficient to capture the depth of a major recession or the peak of a strong expansion; see e.g. Carriero et al. (2020). Fourth, the sources of the shocks and/or the drivers of the crises change over time. For example, they can be related to the oil price, to the accumulation of risks in the financial sector, to self-fulfilling negative expectations, or to external events such as natural disasters or pandemics. This suggests that the variables to be included in the econometric models should also change over time, which can be considered as a special but particularly relevant case of the mentioned parameter change issues. As for parameter changes, it is difficult to specify ex-ante models with changing regressors that produce reliable nowcasts and forecasts.

As it is difficult to implement the first-best solutions to handle forecasting during crises, e.g. specifying a reliable time-varying model with changing indicators over time, a number of second-best approaches have been suggested.

First, we can include an MA term, as in the MIDAS-ARMA and UMIDAS-ARMA models introduced in the previous section. Typically, the use of an MA term reduces the required lag length of the AR polynomial, thus making the model more parsimonious and estimable over short samples. In addition, past errors directly affect the dependent variable and, when combined with positive estimated coefficients, lead to a kind of automated forecast correction. On the other hand, MA terms complicate

Table 1

List of models.

Model	Explanation
midas	MIDAS
midas-AR-mar	MIDAS-AR, where θ is estimated by NLS and other parameters by OLS
midas-AR-mar2	MIDAS-AR, where θ is estimated as in Clements and Galvão (2008)
midas-AR-mar3	MIDAS-AR, where all parameters are estimated by NLS
umidas	UMIDAS
umidas-AR	UMIDAS-AR
midas-ARMA	MIDAS-ARMA, where all parameters are estimated by NLS
midas-ARMA-K2	MIDAS-ARMA with $K = 2$
umidas-ARMA-gls	UMIDAS-ARMA, where all parameters are estimated by GLS
umidas-ARMA-nls	UMIDAS-ARMA, where all parameters are estimated by NLS
umidas-ARMA-nls-K2	UMIDAS-ARMA with $K = 2$
AR	Autoregressive model specified by the Bayesian information criterion

estimation, potentially increasing parameter uncertainty and hence reducing forecast precision.

Second, we can combine forecasts across various specifications for the same model and/or across different models; see e.g. Timmermann (2006) for a review and Kuzin et al. (2013) for applications to nowcasting GDP growth. This simple but effective approach addresses model specification and indicator selection uncertainty. It has the capability of reducing the mean square forecast error (MSFE) with respect to that of the component forecasts when optimal combination weights are used. As these weights can themselves be time-varying and/or different during crises, a simple solution such as the average or median of the alternative nowcasts and forecasts can be a valid choice, and indeed empirically it often performs well (see e.g. again Kuzin et al. (2013) and Timmermann (2006)).

Third, we can modify the estimation method to give a larger weight to observations similar to those expected during the forecast period—the so-called similarity approach (e.g., Dendramis et al. (2020)). Here, the rationale is to try to capture parameters for time variation by using a non-parametric estimator (specifically that developed by Giraitis et al. (2018)). Intuitively, in the simple case of two regimes, say high and low growth, one would like to use the low growth observations exclusively to estimate the model when predicting in a low-growth period. This intuition can be extended and formalized; see Dendramis et al. (2020) and the references therein for details. In our context, we use only observations from the financial crisis and recovery period, the period that is most similar to the Covid-19 period, to estimate the models in Table 1 and to produce nowcasts and forecasts.

Finally, we consider adjusting the forecasts to put them back on track by using a specific form of intercept correction (e.g., Clements and Hendry (1999)). This is a rather ad-hoc approach that is intended to eliminate bias of unknown form from the forecasts by adding to them, typically, the previous period forecast error. Of course, such an addition, when not needed, results in an increase in the MSFE. In our context, we use the nowcast and forecast errors made by the models in Table 1 during the financial crisis and recovery period to adjust the nowcasts and forecasts by the same models for the Covid-19 crisis and recovery, with details provided below.

Another potential issue with similarity and intercept correction is that focusing the evaluation exclusively on

extreme events using standard metrics can bias the results, in the sense of picking models that on average can work very badly; see Lerch et al. (2017). However, we believe that it makes sense to adjust the nowcasts when there is reasonable evidence of being in the midst of a crisis, such as during the Covid-19 episode. In addition, the unprecedented nature of this pandemic crisis raises the need for strong assumptions and judgmental adjustments, especially for the forecasting part; see Primiceri and Tambalotti (2020).

All these methods for forecast improvement during crises share the feature of potentially reducing the forecast bias and increasing the precision in the presence of model mis-specification, such as unaccounted parameter changes or the wrong choice of indicators, when the mis-specification cannot be directly handled by modifying the model. The extent of the expected improvement can hardly be determined analytically and ex-ante, and there are potentially large costs, in particular in terms of the MSFE, if the adjustments are applied when they are not needed. Hence, their effects should be empirically evaluated, as we do in the following sections.

4. Predicting the Covid-19 recession and recovery

In this section we use the models listed in Table 1 with a variety of indicators to produce nowcasts and forecasts of GDP growth for the period 2020Q1–2022Q4 for the US and the other G7 countries. GDP data span the period 1960Q1–2019Q4 for the US, 1981Q1–2019Q4 for Canada, and 1980Q1–2019Q4 for the rest of the G7.

Table 2 summarizes the latest available observations on GDP and IP until the end of April 2020. US data were extracted from the Federal Reserve Economic Data,[4] and the Canadian data came from (Fortin-Gagnon et al., 2018).[5] Data for the other G7 countries were taken from the OECD.[6] All variables were transformed in growth rates by the first difference of logs and presented in percentage terms.

Table 2 reveals the importance of using mixed-frequency data, since the Covid-19 shock has clearly occurred only during the last month of the quarter. This is

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[4] https://fred.stlouisfed.org.

[5] http://www.stevanovic.uqam.ca/DS_LCMD.html.

[6] https://stats.oecd.org.

Table 2
Final values for GDP and IP growth.

		US	DE	FR	IT	UK	JP	CA
GDP	2019Q4	0.53	0.03	−0.05	−0.30	0.02	−1.83	0.14
IP	2020M01	−0.49	2.82	1.09	3.57	−0.10	2.02	0.11
	2020M02	0.46	0.40	0.91	−1.05	−0.10	−0.40	0.11
	2020M03	−5.55	−12.85	−18.14	−33.35	−4.33	−3.69	−4.03

also noted in Diebold (2020). For the sake of conciseness, we only present results for the US case. The detailed results for the rest of the G7 countries are available in the Online Appendix.

4.1. US nowcasts based on IP

Fig. 1 plots the nowcasts and forecasts for the US GDP using all the models in Table 1 and IP as a predictor. While the share of manufacturing in GDP declined over time for the US and the other G7 countries, IP growth is still considered a reliable coincident indicator of GDP growth, and hence we used it as a common explanatory variable in the nowcasting exercises. The average prediction across models was also added, as a standard example of the combination of individual forecasts.[7] The left panel shows the annualized growth, while the implied level forecasts are shown in the right panel.

Most of the models predict a 1.5% fall in GDP annualized growth in 2020Q1. A few are more pessimistic: midas-AR-mar3 and umidas-ARMA-nls-K2 predict a decrease of 6% and 4%, respectively. As the actual (first-released) value of GDP growth by the US BEA for 2020Q1 was −4.8%, the majority of the models produced overly optimistic nowcasts.

When the growth forecasts are transformed in levels, virtually all the models predict that pre-Covid-19 GDP levels will be achieved during 2021, with the most pessimistic ARMA alternative predicting that the economy will be back on track by 2022Q1.

All models, except umidas-ARMA-gls, produce persistent forecasts, such that the pre-2020 trend growth is not achieved even by the end of 2022, where trend growth is defined as that resulting from dynamic forecasts from an AR model estimated with data up to 2019Q4.

4.2. US nowcasts based on other predictors

Other monthly indicators might be useful to nowcast and predict GDP growth. In particular, we consider a subset of those in Carriero et al. (2020), taking the most representative ones among labor market indicators, surveys, credit spreads, and financial indicators. Specifically, we use employment growth, the PMI composite index, the credit spread (BAA minus 10-year treasury), the VIX, and the NFCI (National Financial Conditions Index).[8]

The credit spread and NFCI are included to take into account shocks to the external finance premium and the downside risk in GDP associated with tighter financial conditions; see for example Adrian et al. (2019) and Boivin et al. (2020). The PMI is considered a proxy for economic sentiment, which, in turn, has been suggested as a potential source of business cycle fluctuations; see Angeletos and La'O (2013) and Benhabib et al. (2015). Finally, the VIX is a proxy of uncertainty that might affect investment, employment, and consumption decisions, and therefore might have an important impact on GDP, as pointed out in Bloom (2009).[9]

Fig. 2 reports the growth and level forecasts using employment in the first row. In March 2020, US IP fell by more than 5%, while employment decreased by only 0.5%. Hence, the impact of the Covid-19 pandemic is much more evident when using IP as predictor. With employment, no model predicts negative growth in 2020Q1. But the models are unanimous about the drop in 2020Q2 and subsequent recovery. Pooled nowcasts instead remain overly optimistic, reflecting the views of the majority of models. When transformed in levels, the pre-Covid-19 level is already reached in 2020, except for the MA alternative, which produces the most pessimistic scenario. Yet, the trend growth is not restored: it remains well below pre-Covid-19 levels by the end of 2022. Interestingly, using VIX as a predictor, and paired with UMIDAS models containing the moving average terms, a deep decline is predicted by the end of the current year. Fig. 11 in the Appendix shows the results obtained with all other indicators.

In Fig. 3 we report, for each predictor, the pooled (mean) nowcasts and forecasts from all models using that specific predictor, as a way to summarize the results. Even after averaging out the model instability, we note a lot of disagreement across different predictors. For instance, PMI and NFCI announce no downturn, while using the implied market volatility (VIX) provides the second-most pessimistic forecasts, followed by models using the credit spread.

Overall, we note a lot of instability in predictions across models and predictors. In general, the MA adjustment tends to lower the forecasts, while using PMI and NFCI provides quite optimistic scenarios, likely because both variables were substantially affected by the expansionary monetary and fiscal policies put in place to counter the effects of Covid-19. Forecast combination mitigates the large departures by MA models and gives more stable paths, especially when the VIX and BAA10Y are used as predictors.

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[7] Median forecasts were also considered. We do not report them for sake of simplicity, but the results were very close to the average prediction.

[8] BAA10Y, NFCI, and VIX were taken from the Federal Reserve Economic Data. PMI was downloaded from Quandl. Note that a monthly US GDP proxy is also available (https://ihsmarkit.com/products/us-monthly-gdp-index.html). But the measure is not available as quickly as the industrial production index.

[9] On the other hand, (Rogers & Xu, 2019) find that various uncertainty measures have no forecasting power when assessed in real time.
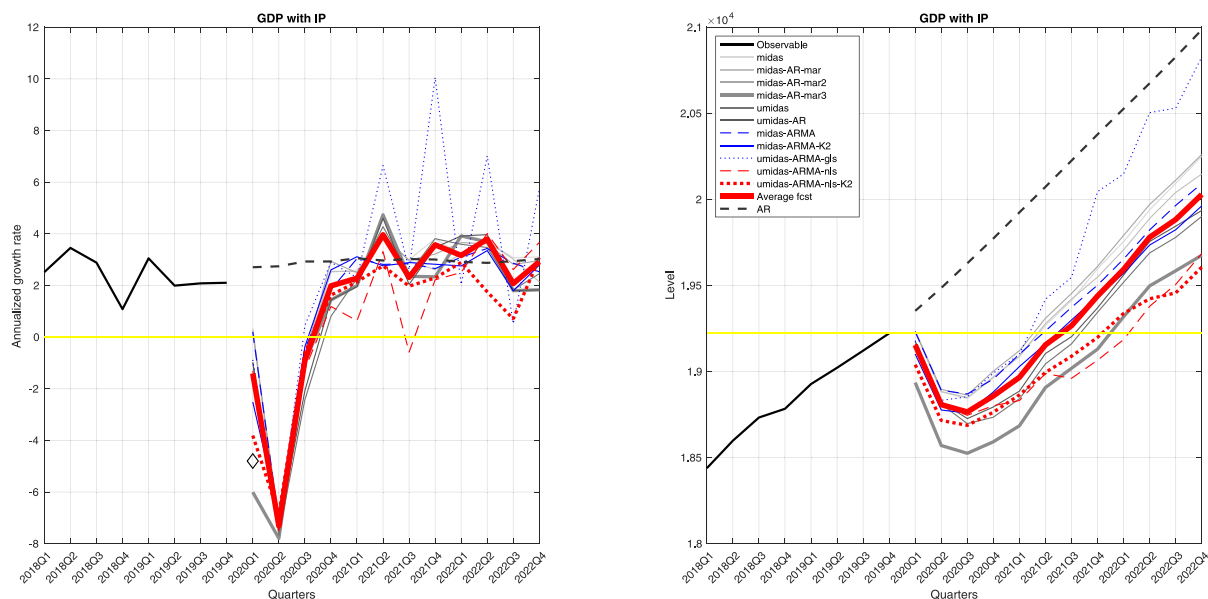
Fig. 1. Actual forecasts of the US Covid-19 recession and recovery. Note: The left panel plots the forecasts of the annualized growth rate, while the right panel shows predicted levels. The models are listed in Table 1.

5. Forecasting the Covid-19 recession and recovery: Lessons from the financial crisis

We now consider the effects of the two adjustments based on the experience of the financial crisis mentioned in Section 3, namely, giving more weight at this period at the estimation stage, or correcting the Covid-19 nowcasts and forecasts by an amount proportional to the nowcast and forecast errors made by the models during the financial crisis and recovery period. In the first subsection we discuss why the financial crisis is a good proxy for training our forecast corrections. Then, we assess the performance of the models during the financial crisis, and compare that to the Covid-19 period. Finally, in the third subsection we evaluate the effects of the adjustments based on the experience of the financial crisis on the Covid-19 nowcasts and forecasts.

5.1. Why use the financial crisis for a Covid-19 forecast correction?

Covid-19 generated very large shocks, as did the financial crisis, and the effects are probably well captured by the usual demand and supply channels. However, the nonlinear and non-proportional effects cannot be captured by standard econometric models, at least not without imposing strong assumptions, as noted in Primiceri and Tambalotti (2020). Therefore, a forecast correction is needed.

Why is the Great Recession associated with the financial crisis a good candidate? Fig. 4 plots the evolution of a few indicators that played major roles during the financial crisis and the subsequent recession and recovery. The financial conditions during the Covid-19 crisis did not deteriorate as much as during the Great Recession, possibly due to the timely reaction of the monetary authority,

as suggested in Boivin et al. (2020). Both producer and consumer sentiment fell, but did not reach the levels seen in 2008, and the price of oil was already decreasing before the pandemic shock. Instead, two uncertainty measures, the VIX and macroeconomic uncertainty, as measured in Jurado et al. (2015), peaked like during the financial crisis, while the Economic Policy uncertainty index of Baker et al. (2016) exploded to a historic level.

Several similarities with the financial crisis can also be observed through the lens of the analysis of the Great Recession by Stock and Watson (2012). First, the collapse following the financial crisis and that following the pandemic were unprecedented in both cases, albeit with the major difference that the trigger was not the same. Nevertheless, both shocks were large and rarely observed in modern history, potentially implying non-proportional and long-lasting effects, as noted above. Second, we are back to a zero lower-bound regime, for the monetary policy and further stimulus are likely to be less effective, implying a slower recovery. Finally, uncertainty played a major role in both recessions, as noted above.[10] (Leduc & Liu, 2020) argue that, since uncertainty shocks provoke effects that are similar to those resulting from declines in aggregate demand, the actual increase in uncertainty will amplify the Covid-19 economic effects, especially with strong increases in unemployment and declines in inflation. In addition, Baker et al. (2020) suggest that almost half of the projected contraction in US GDP in 2020 will be attributed to uncertainty, while (Moran et al., 2020) find that such shocks lead to severe economic downturns, lower inflation, and sizeable accommodating measures from monetary policy.

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[10] As proposed in Bloom (2009), an increase in uncertainty encourages firms to postpone major investment projects and to reduce hiring; consumers likewise postpone purchases of durable goods, and financial institutions restrict their lending activities.
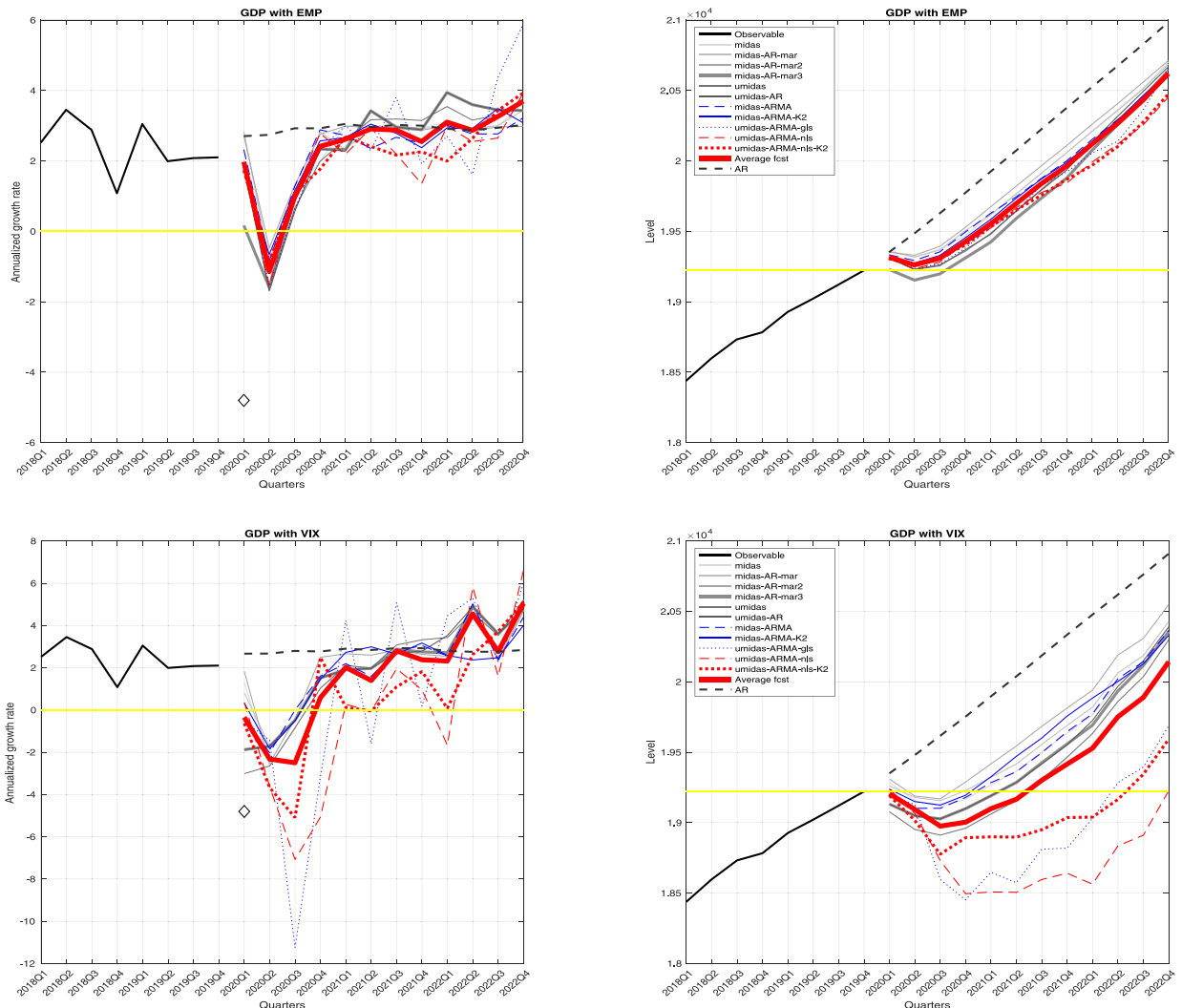
Fig. 2. Actual forecasts of the US Covid-19 recession and recovery: other indicators. Note: see Note to Fig. 1.

In summary, the Great Recession and the Covid-19 crisis differ in terms of the trigger, transmission (as the financial conditions are better in the latter case), and partly in terms of policy responses (stronger and faster in the latter case). Yet, the two crises also share similarities, in particular a major increase in uncertainty, and in terms of the size of the implied demand and supply shocks, the Great Recession is the most similar event to the Covid-19 crisis in the past decades. Hence, the performance of nowcasting models and specific indicators during the Great Recession could be informative for the Covid-19 crisis, which is indeed what we found empirically, at least for 2020Q1.

5.2. Nowcasts and forecasts for the financial crisis period

We use the same models in Table 1 and predictors to forecast GDP during the financial crisis and subsequent recovery, the period 2008Q3–2013Q2. The timing is the following: GDP is observed until 2008Q2, while monthly indicators are known until 2008M09 is included. Hence, it is the same situation in terms of monthly information available within the quarter to be nowcasted. Although the NBER turning point for the US is December 2007, we start from the third quarter of 2008 because this is the set of circumstances most similar to the actual Covid-19 pandemic: industrial production dropped by 4.4% in September 2008 and real GDP started decreasing in 2008Q3. Note that we use historical rather than real-time data in this exercise. Although this might improve the predictive accuracy over the Great recession period, we believe it is more appropriate to use the most recent values, since the goal is to correct the actual forecasts.

Starting with the US, Fig. 5 plots the out-of-sample growth and level nowcasts and forecasts focusing for clarity only on IP, employment, and VIX as predictors. The results for the other predictors are available in Fig. 12 in Appendix. Table 3 reports the MSE and MAE for all models and all indicators, relative to an AR model, over the 2008Q3–2013Q2 period (and hence across different
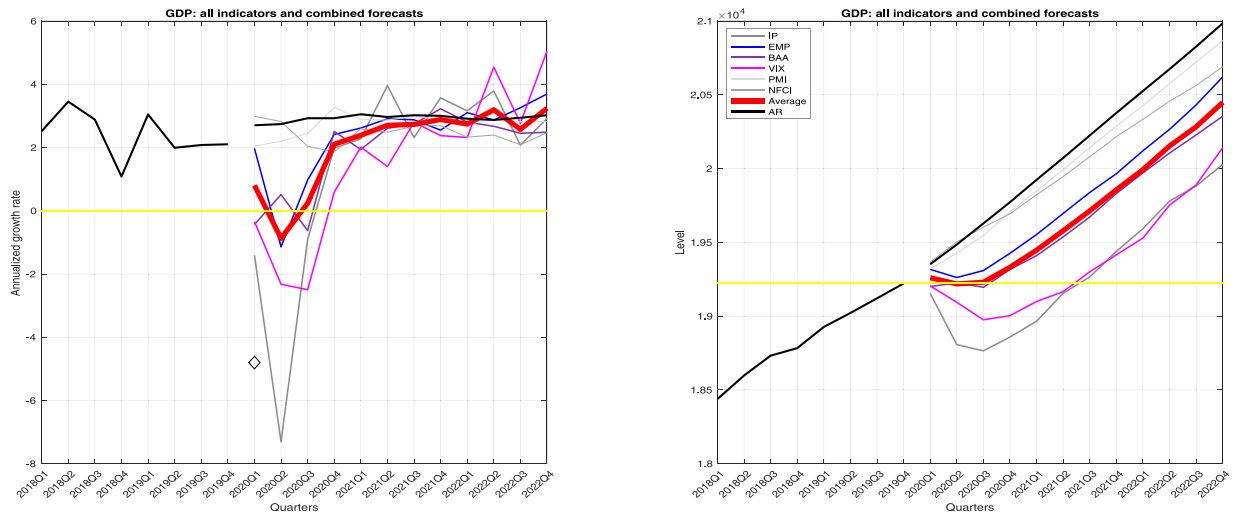
Fig. 3. Actual forecasts of US Covid-19 recession and recovery: combined forecasts. Note: This figure shows, for each predictor, the pooled (mean) nowcasts and forecasts from all models in Table 1.

forecast horizons).[11] A few comments can be made. First, the actual value of GDP annualized growth for 2008Q3 was -2.17. Several models with IP as the indicator returned even more negative nowcasts, while all the models with EMP as the predictor returned (slightly) higher values. Using VIX did not predict any downturn. Second, the actual value for 2008Q4 was even more negative, and in this case even with IP as the predictor, all the forecasting models were a bit too optimistic. The forecasts with EMP as the indicator were substantially out of target. Third, IP predicted a faster recovery than realized, much more so with EMP. Fourth, and in line with the outcome from Figs. 5 and 12, according to Table 3, the best nowcasts and forecasts are produced by models with IP as the indicator rather than EMP. The gains with respect to the AR model are substantial, and the best specifications are UMIDAS and UMIDAS-AR, a with relative MSE of 0.62 and 0.63, respectively. Fifth, including an MA term does not help. Actually, it leads to an increase in the relative MSE of 10% or higher. Instead, forecast combination is comparable to the best single models. The relative MSE is 0.64 for the median and 0.66 for the average of the single forecasts. Finally, the same ranking of models, indicators, and effects of adding MA or pooling emerges when using the MAE instead of the MSE for the evaluation.

To conclude, while monthly information, in our case data on IP, substantially improves nowcasts and forecasts of GDP growth for all the countries under consideration with respect to a quarterly AR model, the depth of the financial crisis was systematically underestimated and the speed of the recovery generally overestimated. Similar performance can be expected for the Covid-19 crisis and recovery. Actually, as we have seen, the models did not capture the drop in GDP growth in 2020Q1 for all countries. Adding an MA term to the models does not lead

to major improvements, forecast combination performs similarly to the best single models but still suffers from the same problems. This leaves similarity estimation and intercept correction as the only possible remedies. Unfortunately, their performance during the financial crisis cannot be evaluated, as there are no previous comparable periods. (In principle one could consider what happened during the Great Depression, but the economy was so different then that the results would not really be comparable.) Therefore, in the next subsection we implement these approaches to modify the 2020Q1 nowcasts and subsequent forecasts, to see whether the precision increases with respect to that obtained from the standard models of the previous section.

5.3. Adjusting Covid-19 recession and recovery forecasts

Fig. 6 compares the GDP growth and level forecasts for the US from Fig. 1 with predictions adjusted by intercept correction or similarity-based estimation. We focus on average forecasts (in bold), with results for other models in dashed lines. Specifically, the intercept-corrected nowcasts and forecasts are obtained for each model and indicator by adding to the unadjusted values in Fig. 1 the nowcast and forecast errors made by the same model for each horizon over the period 2008Q3–2011Q3. For similarity-based estimation, each model is estimated only over the period 2002Q1–2013Q4 and the resulting estimated parameters are used to construct the nowcasts and forecasts for 2020Q1–2022Q4.

The figures highlight that similarity estimation has overall limited effects on the nowcasts and forecasts, whereas the differences are substantial with intercept correction. In case of the IP and EMP predictors, the adjustment does not affect the 2020Q1 nowcast, but the average corrected growth forecasts are lower than the uncorrected ones for each horizon, and more so when employment is used as a predictor. As a consequence, there are even larger differences between the corrected

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[11] We do not present statistical tests for the significance of the differences in the MSE and MAE across models due to the short sample size, which makes any test unreliable due to very low power.

(a) Financial conditions
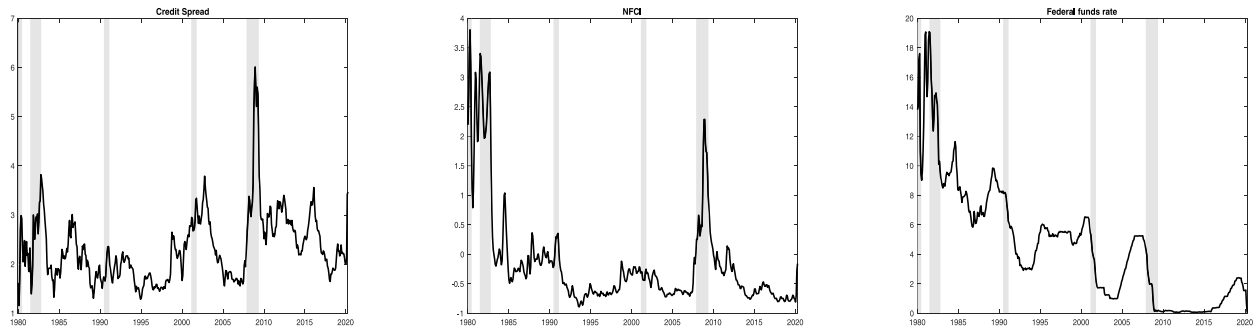
(b) Uncertainty measures
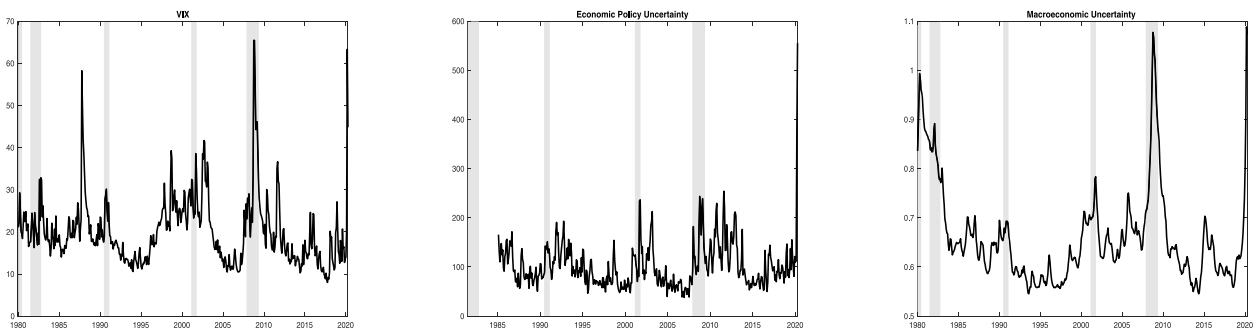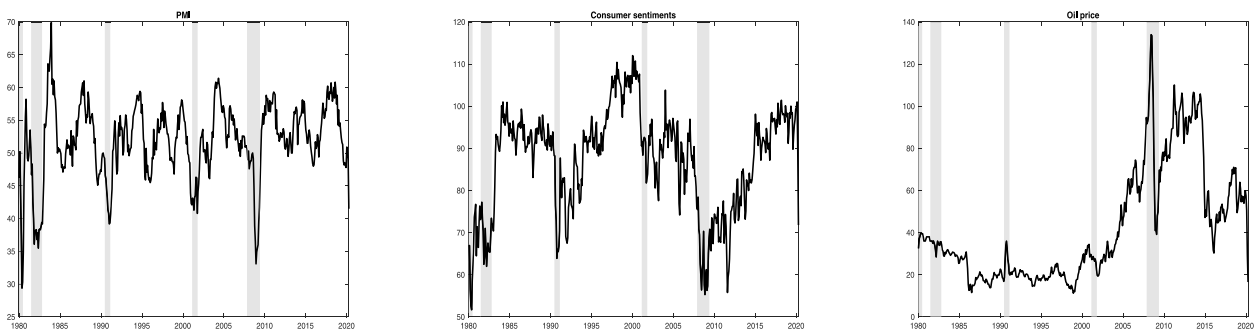

(c) Sentiments and oil price

Fig. 4. Evolution of economic and financial conditions.

and uncorrected forecasts for GDP levels, with the former suggesting that pre-Covid-19 levels will not be reached even by the end of 2022.

Interestingly, when the credit spread and stock market volatility are used as indicators, the average corrected nowcast for 2020Q1 gets much closer to the actual (first-released) value of GDP growth than the average unadjusted nowcast. The similarity approach provides substantial adjustments for forecasts made using VIX, PMI, and NFCI, and especially at longer horizons for the last two indicators (see Fig. 13 in the Appendix). This suggests that the role of these variables changes during crises, and estimation over shorter periods dominated by a crisis makes them more important, improving the

nowcasts and forecasts during similar subsequent times of crisis.

Another interesting effect of the correction is that it makes all the nowcasts and forecasts much more similar to each other. A principal component analysis of the standard and intercept-corrected alternative nowcasts and forecasts across all predictors and models, shown in Fig. 7, indicates that the first component explains 65% of their variability, with the value increasing to more than 94% after correction. This suggests that the nowcast and forecast differences across models during the Covid-19 period are similar to those during the financial crisis period, and therefore these differences shrink after the adjustment.

It is also worth mentioning that, due to the direct forecasting approach and the need to estimate some nonlinear
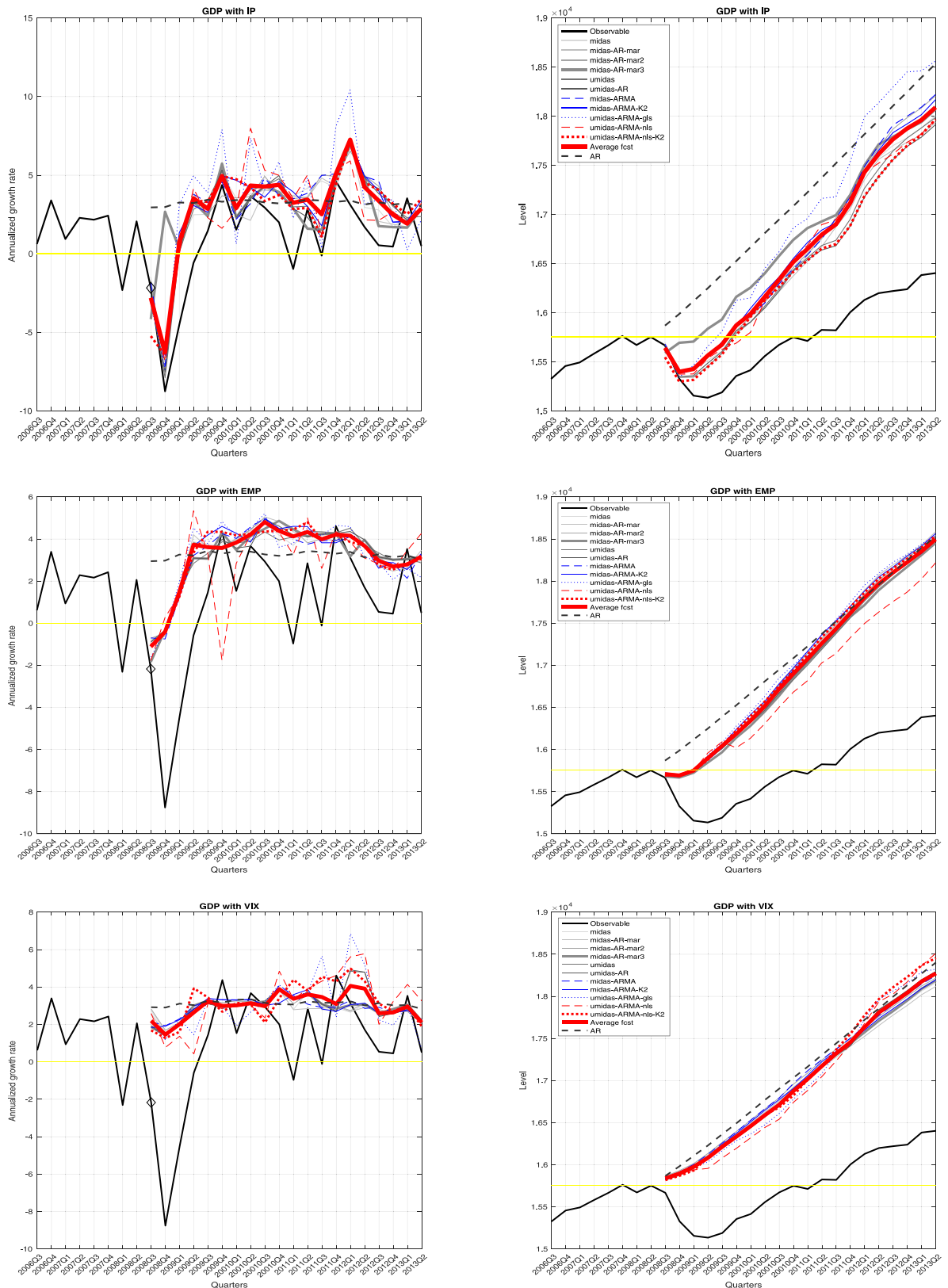
Fig. 5. Out-of-sample forecasts of the US Great Recession and recovery. Note: see Note to Fig. 1.
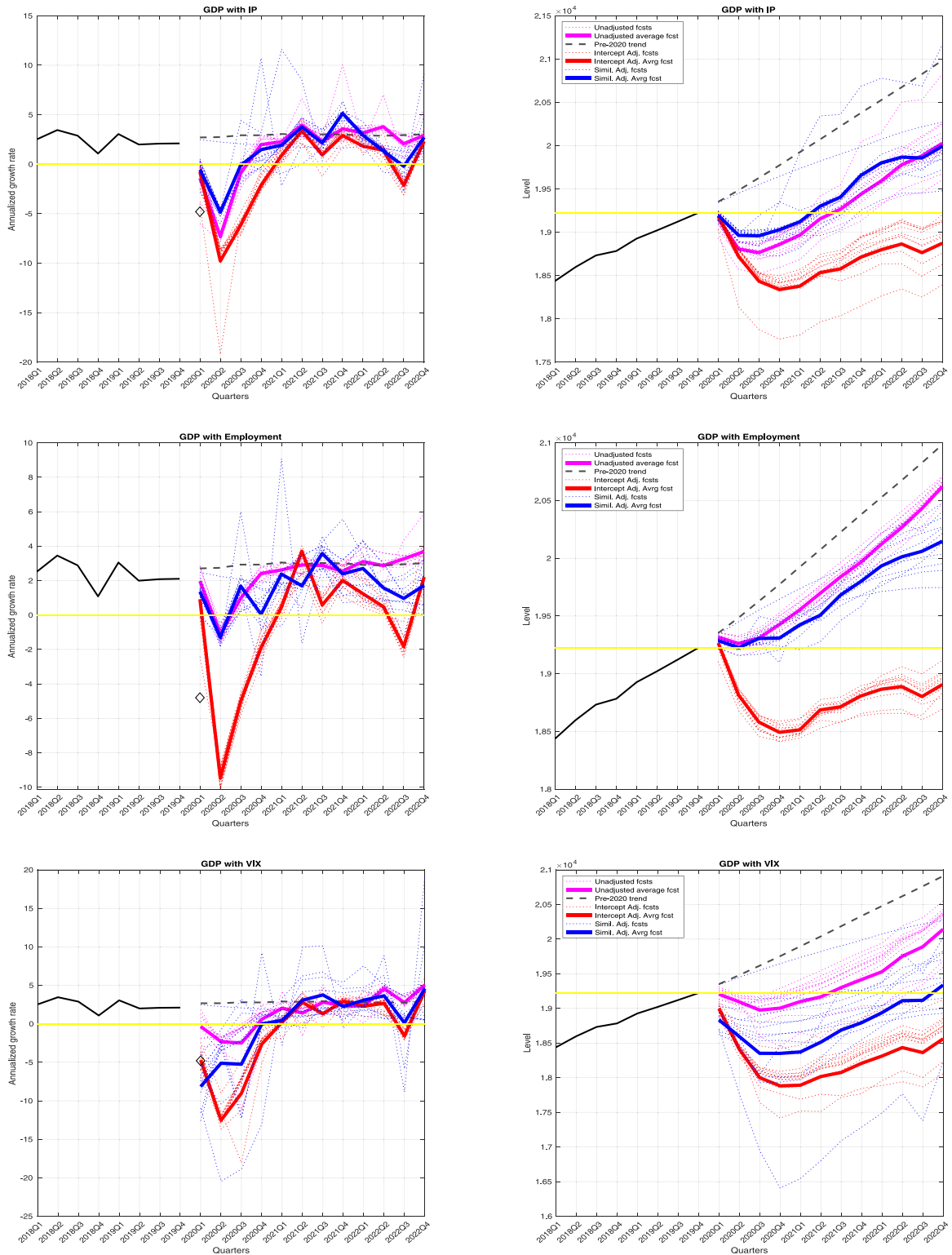
Fig. 6. Adjusted forecasts of the US Covid-19 recession and recovery. Note: This figure plots the US GDP growth and levels using original forecasts and predictions adjusted by intercept correction and similarity.

Table 3
Relative predictive accuracy: US with all indicators.

Models	IP		EMP		BAA10Y	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
AR	3.90	2.74	3.90	2.74	3.90	2.74
midas	0.65	0.74	0.84	0.96	0.91	0.88
midas-AR-mar	0.68	0.79	0.86	0.99	0.92	0.88
midas-AR-mar2	0.72	0.84	0.85	0.98	0.94	0.93
midas-AR-mar3	0.88	0.90	0.84	0.89	0.91	0.90
umidas	**0.62**	**0.74**	0.83	0.92	0.84	0.84
umidas-AR	0.63	0.74	0.84	0.93	0.85	0.87
midas-ARMA	0.72	0.83	0.80	0.90	0.96	0.93
midas-ARMA-K2	0.73	0.86	0.85	0.96	0.91	0.90
umidas-ARMA-gls	0.91	1.09	0.85	0.93	0.86	0.89
umidas-ARMA-nls	0.70	0.86	0.96	1.02	0.98	0.97
umidas-ARMA-nls-K2	0.68	0.82	0.84	0.94	0.86	0.89
Median fcst	0.64	0.75	0.84	0.94	0.90	0.89
Average fcst	0.66	0.80	0.84	0.95	0.90	0.89
Models	VIX		PMI		NFCI	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
AR	3.82	2.65	3.90	2.74	3.78	2.62
midas	0.90	0.95	0.91	0.94	0.95	0.97
midas-AR-mar	0.90	0.93	0.92	0.95	0.95	0.97
midas-AR-mar2	0.92	0.96	0.91	0.94	0.93	0.94
midas-AR-mar3	0.90	0.94	0.91	0.95	0.94	0.99
umidas	0.91	1.00	0.85	0.91	0.89	0.92
umidas-AR	0.91	1.00	0.86	0.91	0.89	0.92
midas-ARMA	0.93	0.95	0.91	0.94	0.93	0.95
midas-ARMA-K2	0.92	0.95	0.91	0.95	0.95	0.98
umidas-ARMA-gls	0.96	1.03	0.84	0.93	1.11	1.17
umidas-ARMA-nls	0.92	1.02	0.98	1.09	1.07	1.25
umidas-ARMA-nls-K2	0.95	1.04	0.87	0.96	0.94	0.99
Median fcst	0.90	0.95	0.91	0.95	0.95	0.98
Average fcst	0.91	0.97	0.89	0.94	0.92	0.98

Note: This table reports the MSE and MAE based on the 2008Q3–2013Q2 period (and hence across different forecast horizons).

(MIDAS) models, the estimation sample for the similarity approach has to be long enough, longer than the Great Recession and recovery period on which we would like to focus. To assess whether this is a relevant issue, we also performed similarity correction only for the nowcasts by estimating the models over the shorter 2008Q1–2011Q3 window. It turns out that this similarity correction moves the nowcasts for 2020Q1 further in the right direction, with their average very close to the actual GDP growth when IP is used as the predictor; see Table 4.

Table 5 summarizes all our forecasts for the G7 countries for 2020 and 2021, and compares them to the International Monetary Fund (IMF) predictions released in June and October, and to consensus forecasts (mean) based on surveys also conducted in June and October.[12] We report the median, minimum , and maximum forecasts for the unadjusted, intercept, and similarity cases.[13] The lines labeled "IMF" and "Consensus" report the forecasts published respectively by IMF and by consensus forecasts. A few interesting features emerge from this table. First, there is a fair amount of model uncertainty as reported by minimum and maximum forecasts. For instance, even

after intercept correction, the predicted annual growth for the US in 2021 ranges between −8.49% and −3.65%. Second, we remark that the June IMF predictions for 2020 are close to our most pessimistic forecasts (the closest forecasts to the IMF predictions are in bold), whereas in 2021, they are in line with our most optimistic outcomes. Their update in October yields predictions much closer to our median intercept-adjusted forecasts. Finally, the consensus forecasts for 2020 are more optimistic than those from the IMF for all countries, and within the min–max ranges of our intercepted-adjusted forecasts for all countries, except Japan. For 2021, the consensus forecasts are broadly in line with those from the IMF, and generally more optimistic than ours (and even larger than the max value for the intercept-adjusted forecasts for Italy, France, and Canada).

Finally, we apply the same intercept correction to the New York Fed (NYFED) and Survey of Professional Forecasters (SPF) nowcasts and forecasts of 2020.[14] These predictions were made at the end of 2020Q1. New York Fed Staff produce only the nowcast of the current quarter and one-step-ahead forecast, while the SPF provide the nowcast and forecasts for up to four quarters. Results

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[12] The IMF report can be found at https://www.imf.org/en/Publications/WEO/Issues/2020/06/24/WEOUpdateJune2020.

[13] Note that a more formal analysis of uncertainty for the intercept- and similarity-adjusted predictions could in principle be obtained by a bootstrap procedure.

[14] New York Fed Staff Nowcasts and SPF can be found at https://www.newyorkfed.org/research/policy/nowcast and https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/survey-of-professional-forecasters, respectively.
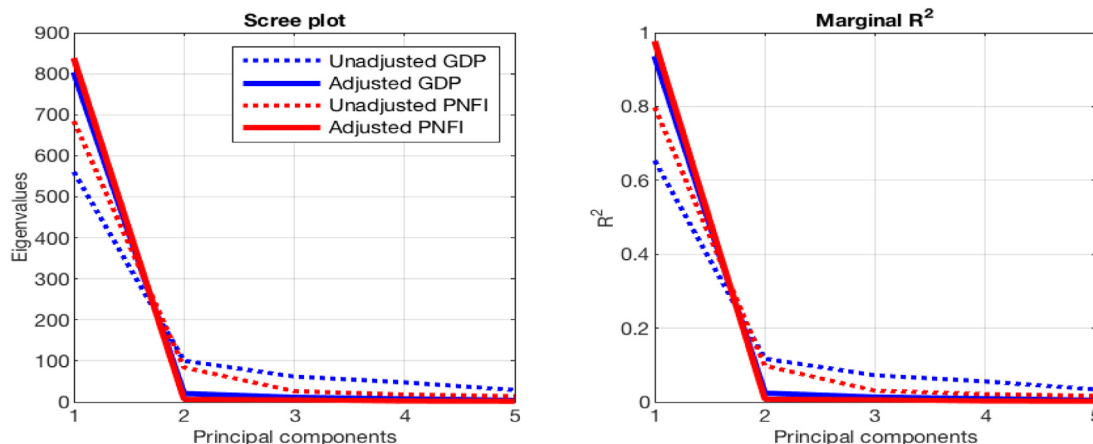
Fig. 7. Factor structure of unadjusted and adjusted forecasts. Note: The left panel plots the highest eigenvalues of the correlation matrix of all unadjusted and intercept-adjusted forecasts of both US GDP and investment. The right panel shows the average explanatory power of first five principal components on those forecasts.

Table 4
Nowcasting 2020Q1 US GDP.

	IP	EMP	BAA10Y	VIX	PMI	NFCI
Unadjusted average fcst	−1.33	1.98	−0.43	−0.34	2.06	2.99
Intercept-adj avg fcst	−0.54	0.91	−2.91	−4.66	−1.45	−0.94
Similarity-adj avg fcst	**−4.22**	−0.63	1.23	−7.56	−0.67	−0.58

Note: This table shows the 2020Q1 nowcasted values of GDP annualized growth rates. In the similarity correction, the models were estimated on the 2008Q1–2011Q3 window.

are displayed in Table 6. The intercept correction adjusts the forecasts in the same manner as with our mixed-frequency models. The 2020Q1 nowcasts get much closer to the realization, while the predicted values of the rest of the year become more pessimistic. This shows that the intercept correction can also be successfully applied to external predictions.

6. Predicting Covid-19 effects on investment

As business cycle fluctuations are typically driven by those in private investment, we assessed normal and adjusted Covid-19 nowcasts and forecasts for the US real private nonresidential fixed investment (PNFI). Fig. 8 plots the PNFI nowcasts and forecasts using all the models in Table 1 and IP as the predictor. Again, the left panel shows the annualized growth rate, and the level forecasts are in the right panel.

All models predict an important decrease of the US investment growth in the first quarter of 2020. The most pessimistic is midas-AR-mar3, with a nowcast of −18%, followed by MA alternatives such as umidas-ARMA-nls-K2 and midas-ARMA-K2, with nowcasts of −12% and −11%, respectively. These values turn out to be too pessimistic, while the average forecast corresponds almost exactly to the actual observed decrease of −8.2%.

Most of the models, and averaging, predict a quite persistent effect of the pandemic shock, since pre-Covid-19 PNFI levels will be only achieved during 2022. The most pessimistic model is midas-AR-mar3, while umidas-ARMA-gls is the only model predicting a rapid V-shape scenario with strong recovery already in 2021.

Figs. 14 and 15 in the Appendix report the nowcasts and forecasts for PNFI using all other predictors. In general, they are all more optimistic than when using IP as the indicator, and too much so. As it was the case for GDP, the PMI and NFCI announce barely no downturn, except when using some models with MA terms. The same MA adjustment, when combined with the BAA10Y and VIX as indicators, leads to persistent and more pessimistic expected paths for investment.

We now inspect the predictive performance during the Great Recession. The timing is the same as with GDP: the forecasting period is 2008Q3–2013Q2, while PNFI and the predictors are supposed to be observable until 2008Q2 and 2008M09, respectively. Fig. 9 shows the out-of-sample growth and level nowcasts and forecasts using IP as the indicator. The real PNFI decreased by 7.4% in 2008Q3, and all models returned even more negative nowcasts. But, they all failed to predict the huge drop in 2009Q1, and hence suggested an overly optimistic recovery. The performance of all other predictors is reported in Figs. 16–17 in Appendix. Using employment and credit spread produced quite accurate nowcasts for the 2008Q3 period, but all models remained too optimistic for the rest of the recession and the subsequent recovery.

Table 7 in the Appendix summarizes the performance of the models and all predictors in terms of the RMSE and MAE, relative to an AR model, over the 2008Q3–2013Q2 period. The best predictor is clearly IP, followed by employment, while the best model is midas-AR-mar with substantial improvements with respect to the autoregressive benchmark (RMSE 0.54, MAE 0.57). As was the case with GDP, combining forecasts is often the second-best

Table 5
Yearly forecasts and comparison to IMF scenarios.

	G7	US	DE	FR	IT	UK	JP	CA
2020								
Min	−4.73	−3.86	−5.82	−10.06	−10.62	−0.90	−0.86	−1.00
Unadjusted	−3.03	−1.80	−3.10	−8.50	−7.83	−0.35	0.52	−0.17
Max	−0.87	−0.79	−1.33	−5.88	−1.21	0.48	1.48	1.14
Min	−9.70	−8.49	−10.82	−7.59	−10.04	−8.95	−14.11	−7.92
Intercept	−5.33	−4.31	−6.03	−2.68	−4.49	−6.20	−9.90	−3.72
Max	−3.61	−3.65	−4.46	−0.40	−2.47	−3.61	−8.30	−2.37
Min	−6.46	−2.83	−4.91	−3.92	−26.21	−1.18	−2.50	−3.64
Similarity	−3.06	−1.11	−2.84	1.35	−18.91	1.12	−0.45	−0.58
Max	2.70	2.80	2.58	7.69	−5.23	4.94	3.35	2.75
IMF (June)	−9.36	−8.00	−7.80	−12.50	−12.80	−10.20	−5.80	−8.40
IMF (Oct.)	−7.6	−4.3	−6.0	−9.8	−10.6	−9.8	−5.3	−7.1
Consensus (June)	−7.14	−5.43	−6.30	−8.20	−9.87	−7.88	−5.55	−6.78
Consensus (Oct.)	−7.2	−4.0	−5.5	−9.5	−9.9	−10.1	−5.7	−5.8
2021								
Min	−0.89	1.26	−0.30	−2.25	−3.26	−0.23	−3.22	1.77
Unadjusted	1.40	2.92	2.15	−1.05	1.70	0.88	0.68	2.51
Max	4.07	5.70	3.96	3.60	7.87	2.17	1.66	3.54
Min	0.92	−0.50	1.64	−0.27	−0.20	0.96	2.46	2.36
Intercept	3.31	2.08	4.68	2.51	2.05	3.87	4.46	3.54
Max	5.93	4.47	7.49	5.62	4.55	7.51	7.03	4.84
Min	−5.73	0.66	−3.59	−7.01	−21.67	−3.33	−3.40	−1.75
Similarity	−0.40	3.11	1.86	−1.62	−8.64	2.07	−0.37	0.78
Max	5.43	7.49	7.23	5.71	4.26	4.18	5.99	3.17
IMF (June)	5.30	4.50	5.40	7.30	6.30	6.30	2.40	4.90
IMF (Oct.)	4.6	3.1	4.2	6.0	5.2	5.9	2.3	5.2
Consensus (June)	5.18	4.26	5.19	6.75	6.30	6.07	2.42	5.29
Consensus (Oct.)	4.7	3.7	4.4	6.7	5.3	5.7	2.5	4.9

Note: This table shows the average yearly forecasts for 2020 and 2021 from the unadjusted, intercept-, and similarity-corrected scenarios. For each case, the minimum, median, and maximum predictions are reported. Lines labeled "IMF" and "Consensus" report the IMF and consensus predictions, respectively.

Table 6
Applying intercept correction to professional forecasts.

	NYFED		SPF (median)		SPF (mean)	
	Original	Intercept-adj.	Original	Intercept-adj.	Original	Intercept-adj.
2020Q1	1.68	−1.44	1.66	−1.66	1.68	−1.84
2020Q2	0.27	−11.01	2.10	−7.36	2.12	−7.30
2020Q3			2.02	−4.07	2.10	−3.75
2020Q4			2.13	−0.56	2.12	−0.53

Note: This table shows the original and intercept-adjusted New York Fed and Survey of Professional Forecasters nowcasts and forecasts, made available at the end of 2020Q1.

option, while the MA adjustment is only sometimes beneficial.

Fig. 10 compares the intercept- and similarity-adjusted nowcasts and forecasts to the unadjusted ones in Fig. 8. Both corrections are performed in exactly the same way as in the case of GDP predictions. Similarity adjustment does not play a major role, while intercept correction delivers a very precise nowcast for 2020Q1 and deepens the recession in terms of annualized growth rate, prolonging the expected return to the pre-Covid-19 level of investment. Figs. 18 and 19 in the Appendix report the results for all other predictors. The story is similar when employment is used, while intercept adjustment successfully corrects the 2020Q1 nowcast provided by the credit spread. Both corrections do well in terms of nowcasting with VIX.

7. Conclusions

In this paper, we assessed simple methods of improving GDP growth nowcasts and forecasts obtained by mixed-frequency MIDAS and UMIDAS models with a variety of monthly indicators during the Covid-19 crisis and recovery period, such as combining forecasts across various specifications for the same model and/or across different models, extending the model specification by adding MA terms, enhancing the estimation method by taking a similarity approach, and adjusting the forecasts to put them back on track using a specific form of intercept correction.

Among all of these considered methods, adjusting the original nowcasts and forecasts by an amount similar to the nowcast and forecast errors made during the financial crisis and subsequent recovery seemed to produce
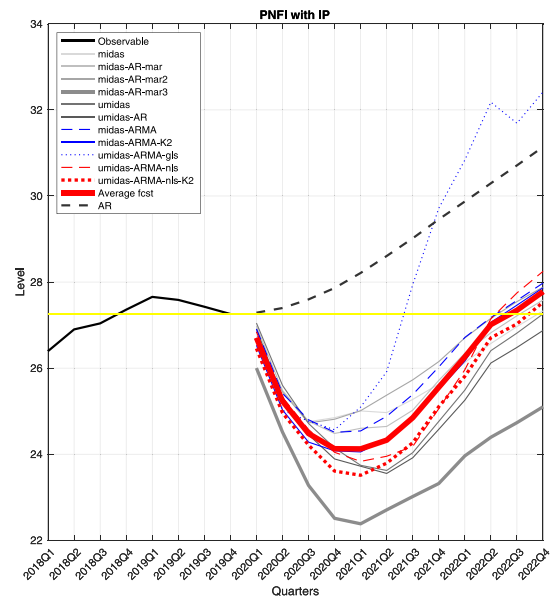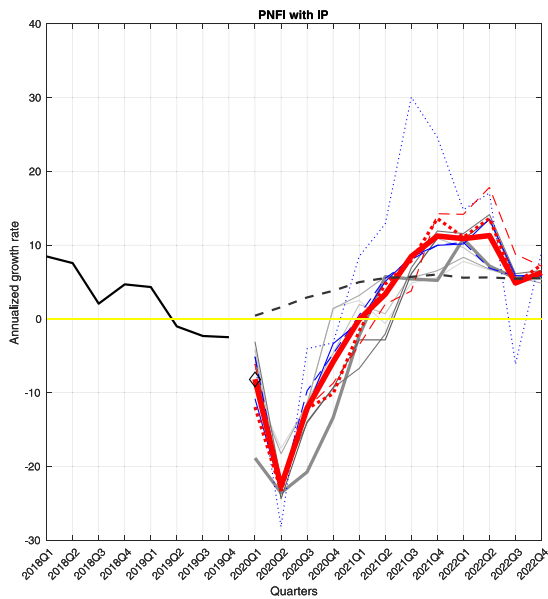
Fig. 8. Actual forecasts of Covid-19 recession and recovery: US investment. Note: see Note to Fig. 1.
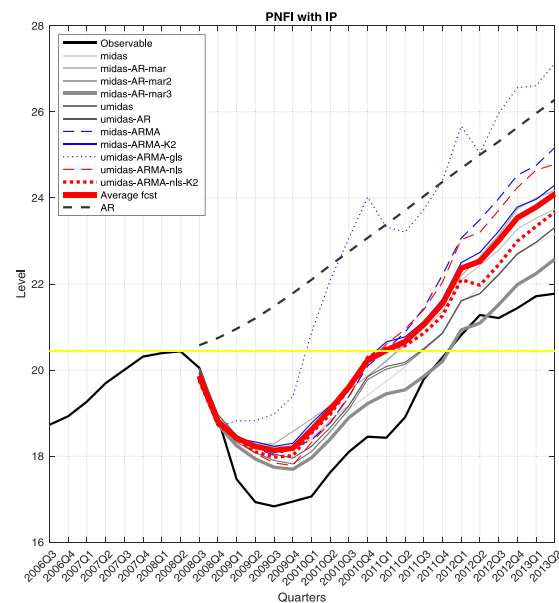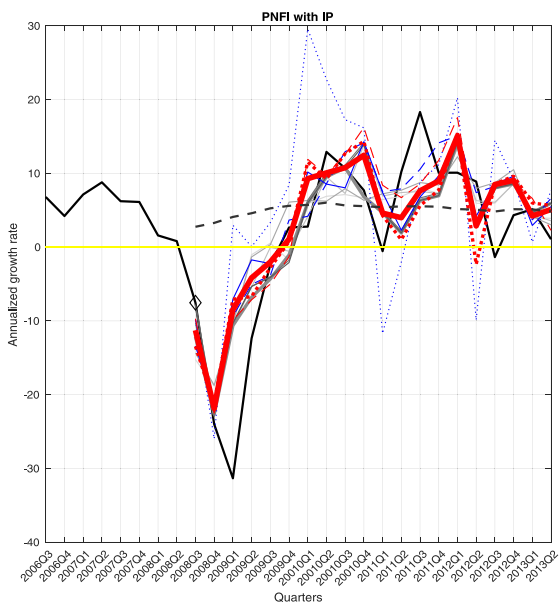

Fig. 9. Out-of-sample forecasts of the Great Recession and recovery: US investment. Note: see Note to Fig. 1.

the best results for the US, notwithstanding the different source and characteristics of the financial crisis. In particular, the adjusted growth nowcasts for 2020Q1 get closer to the actual value, and the adjusted forecasts based on alternative indicators become much more similar, all unfortunately indicating a much slower recovery than without adjustment, and very persistent negative effects on trend growth.

Similar findings also emerged for the other G7 countries in terms of the bias of the unadjusted Covid-19 growth nowcasts and forecasts, and the ranking and effects of the various adjustment methods, with some interesting cross-country differences, such as the expected

faster recovery in Germany and slower recovery in France, Italy, and the UK.

The results were also similar for US private investment, a main driver of business cycle fluctuations. IP turned out to be the most reliable indicator, given our timing, and intercept adjustment produced a precise nowcast for 2020Q1 and lowered the forecasts for the subsequent two-year period, in line with those for GDP growth.

Our analysis could be extended in various directions, such as considering other monthly or even weekly indicators, evaluating more sophisticated econometric models and forecast combination techniques, using real-time data, or assessing the effects not only on point but also
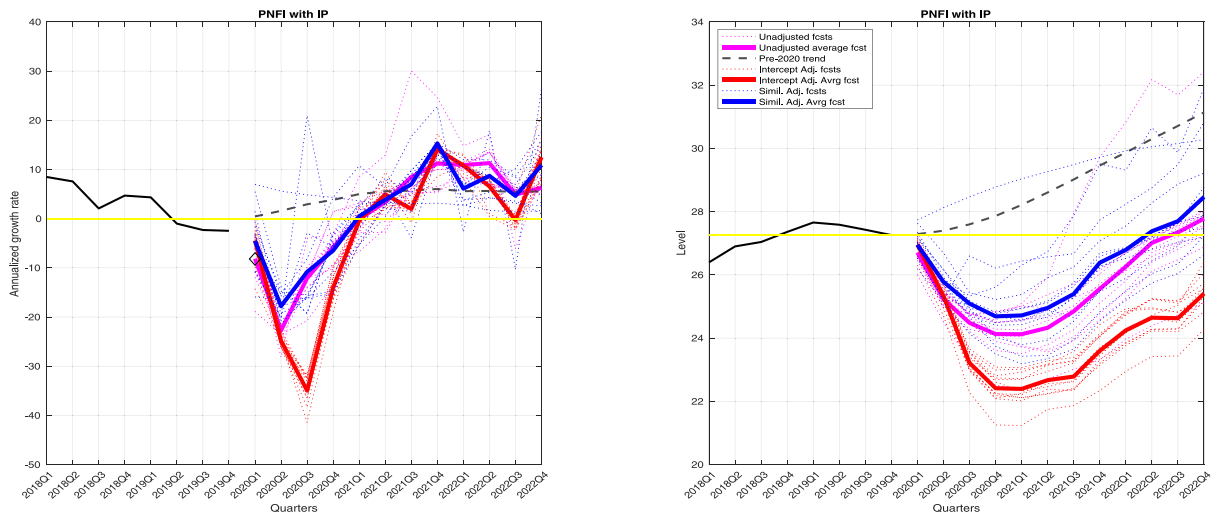
Fig. 10. Adjusted forecasts of Covid-19 recession and recovery: US investment. Note: This figure plots US investment growth and levels according to the original forecasts and predictions adjusted by intercept correction and similarity.

on interval and density forecasts. Yet, based on previous experience with the financial crisis and even milder recessions, we expect all these extensions to have only second-order effects on the main conclusion of our paper: in the presence of major shocks to the economy, only carefully designed external adjustments to nowcasts and forecasts can improve their reliability.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Online appendix: Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ijforecast.2020.12.005.

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