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 by a specific form of intercept correction. Among all these methods, adjusting the original nowcasts and forecasts by an amount similar to the nowcast and forecast errors made during the financial crisis and following 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 emerge also for the other G7 countries.

*The views expressed in this paper are those of the authors and do not necessarily coincide with the views of the European Central Bank or the Eurosystem.

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1 Introduction

Nowcasting and short term forecasting 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 period 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 in correctly predicting the depth of past US recessions and, in particular of the Covid-19 recession, see for example Carriero et al. (2020) and Plagborg-Møller et al. (2020), or An and Loungani (2020) for an analysis of the past performance of the Consensus Forecasts.

Given this evidence, the goal of this paper is to consider simple methods that can improve the 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 following 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 back on track by 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 one, but the specification of such a model would be very complex, as well as its estimation with 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 their usefulness and reliability have to be carefully assessed.

In terms of nowcasting models, we consider standard and unrestricted MIDAS specifications (see e.g. Ghysels et al. (2004), Clements and Galvão (2008), and Foroni et al. (2015)) for quarterly GDP growth, with commonly used monthly indicators (industrial production, employment, surveys, spreads, etc.), direct forecasting when the forecast horizon is larger than one quarter (e.g., Marcellino et al. (2006)), and a representative timing. Specifically for the Covid-19 event, 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 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 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), which suggests that the forecasted fast recovery could also not take place (as it also happened after the financial crisis). All this justifies the need for nowcast and forecast improvement.

Among all 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 following 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 Q1 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 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. The cross-country heterogeneity is evident also 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 of the US investment growth in the first quarter of 2020. The most reliable indicator turns out to be 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 crisis time. Section 4 evaluates the performance of the models during the Covid-19 crisis. Section 5 considers forecasts and errors for the financial crisis periods and uses that information to modify the nowcasts and forecasts for the Covid-19 crisis and recovery. Section 6 repeats the whole analysis for private investment, a key driver of business cycle fluctuations. Section

[1] Carriero et al. (2020), conducting a real time evaluation with weekly updates of the nowcasts, also find that substantial changes in the nowcasts for 2020Q1 take place when information about March starts being used.

7 summarizes the main results and concludes. Additional empirical results are reported in the Appendix.

2 Forecasting models with mixed-frequency data

Let us define $t = 1, ..., T$ as the low frequency (LF) time unit and $t_m = 1, ..., T_m$ 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:

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

where $t_m = m, 2m, ..., T_m$, h_m is the forecast horizon (we use the direct forecasting approach), and the error term u_{t_m} is white noise with $\mathrm{E}(u_{t_m}) = 0$ and $\mathrm{E}(u_{t_m}u'_{t_m}) = \sigma_u^2 < \infty$. Equation (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 an UMIDAS-AR. 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 $\delta(L)$:

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

where

$$\begin{aligned} B(L,\theta) &= \sum_{j=0}^{K} b(j,\theta)L^j, \\ b(j,\theta) &= \frac{exp(\theta_1 j + \theta_2 j^2)}{\sum_{j=0}^{K} exp(\theta_1 j + \theta_2 j^2)}, \end{aligned}$$

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

[2]While multiple indicators are possible from a theoretical point of view, typically in the MIDAS literature single indicator models are used to simplify estimation, and the resulting forecasts are then combined to take into consideration the entire information set. We follow this approach also in the UMIDAS context for comparability.

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

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 Forecast improvements for crisis time

It is well known that, unfortunately, the reliability of forecasts from econometric models decreases during crisis time 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 crisis time, which translates into changes in the model parameters. If a constant parameter model is used, as it is common in the nowcasting literature, its performance will deteriorate, particularly so when the parameters change most, i.e., during crisis time. 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 crisis time (and often also changes during normal times). This suggests to allow 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. Clark (2011) and Carriero et al. (2015). Yet, it is in general insufficient to capture the depth of major recessions and the peak of strong expansions, 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-fulling 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 crisis time discussed above, e.g. specifying a reliable time-varying model with changing indicators over time, a number of second best approaches have been suggested.

First, the inclusion of 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 affect directly 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 estimation, potentially increasing parameter uncertainty and hence reducing forecast precision.

Second, the combination of forecasts across various specifications for the same model and/or across different models (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 be themselves time-varying and/or different during crisis time, 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 Timmermann (2006) and Kuzin et al. (2013)).

Third, the modification of 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 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 only to estimate the model when predicting in a low-growth period. This intuition can be extended and formalized, see Dendramis et al. (2020) and references therein for details. In our context, we will use only observations from the financial crisis and recovery period, the most similar to the Covid-19 period, to estimate the models in Table 1 and produce nowcasts and forecasts.

Finally, the adjustment of the forecasts to put them back on track by a specific form of intercept correction (e.g., Clements and Hendry (1999)). This is a rather ad-hoc approach that is

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
	2020M01	-0,49	2,82	1,09	3,57	-0,10	2,02	0,11
IP	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

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 will 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.

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

4 Predicting the Covid-19 recession and recovery

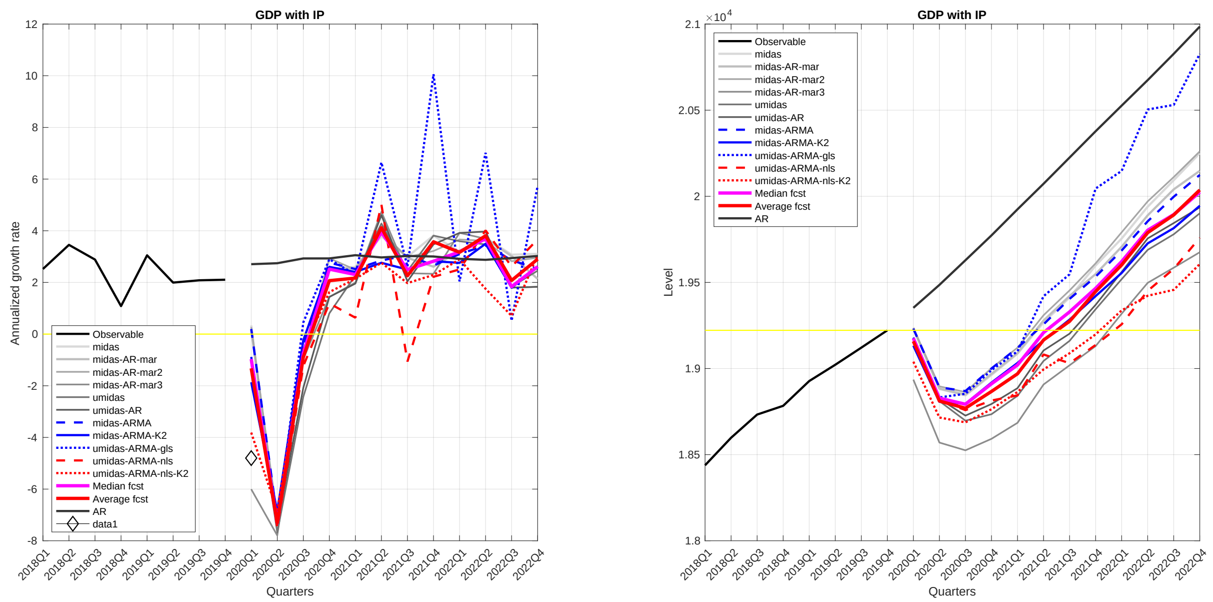
In this section we use the models of Table 1, with a variety of indicators, to produce nowcasts and forecasts of GDP growth for the period 2020Q1-2022Q4 for the US and the other G7 countries. For the US, GDP data span the period 1960Q1 - 2019Q4, for Canada 1981Q1 - 2019Q4 and for the rest of G7 1980Q1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

Table 2 summarizes the latest available observations on GDP and IP by the end of April 2020. US data are extracted from the Federal Reserve Economic Data[3] while the Canadian data come from Fortin-Gagnon et al. (2018)[4]. Data for the other G7 countries are taken from the OECD[5]. All variables are transformed in growth rates by the first difference of logs.

We can see from table 2 the importance of using mixed-frequency data since the Covid-19 shock has clearly occurred only during the last month of the quarter.

[3] https://fred.stlouisfed.org
[4] http://www.stevanovic.uqam.ca/DS_LCMD.html
[5] https://stats.oecd.org

Figure 1: Actual forecasts of COVID recession and recovery



4.1 US nowcasts based on IP

Figure 1 plots the nowcasts and forecasts for the US GDP using all the models in Table 1 and IP as a predictor. The average and median predictions across models are also added, as standard examples of combination of individual forecasts. The left panel shows the annualized growth, while the implied level forecasts are on the right panel.

Most of the models predict a 1.5% fall of the GDP annualized growth in 2020Q1. Few are more pessimistic: midas-AR-mar3 and umidas-ARMA-nls-K2 with decreases 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 too optimistic nowcasts.

When the growth forecasts are transformed in levels, virtually all the models predict that the pre-Covid level of GDP will be achieved during 2021, with the most pessimistic ARMA alternative that brings the economy back on track only at 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.

4.2 US nowcasts based on other predictors

Other monthly indicators might be useful to nowcast and predict the 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 the employment growth, the PMI composite index, the credit spread (BAA minus 10-year treasury), the VIX, and the NFCI (National Financial Conditions Index).

Figures 2 and 3 reports the growth and level forecasts using employment in the first row. In March 2020, US IP has fallen by more than 5% while employment has 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 they are unanimous about the drop in 2020Q2 and subsequent recovery. Interestingly, when the moving average term is included as in umidas-ARMA-nls, it predicts an additional and deep decline by the end of the current year. Pooled nowcasts remain instead too optimistic, reflecting the views of the majority of models. When transformed in levels, the pre-Covid level is reached already in 2020, except for that MA alternative that produces the most pessimistic scenario. Yet, the trend growth is not restored, it remains well below the pre-Covid by the end of 2022.

In Figure 4 we report, for each predictor, the pooled (mean and median) 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. Forecast combination mitigates the large departures by MA models and gives more stable paths, especially when VIX and BAA10Y predictors are used.

4.3 G7 nowcasts based on IP

Figures 5 and 6 present nowcasts and forecasts for, respectively, GDP growth and levels using the models in Table 1 and IP as predictor. The results are rather heterogenous across countries, with marked drops for France, Italy and UK, a decline in Germany comparable to that expected for the US, and very limited effects on Japan.

The cross-country heterogeneity is evident also in the forecasts, with the first group of countries experiencing a very slow recovery, Germany a faster recovery (comparable to the US) but with a new slowdown predicted for 2022, 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.[6]

In terms of the effects of having MA terms in the model, they tend to lower the nowcast for 2020Q1 for almost all countries, and especially for Germany. They also exacerbate the persis-

[6] Although it is standard practice to use industrial production as an indicator to nowcast GDP, there is an even better indicator in the case of Canada, an official monthly estimate of GDP by industry (GDPmonth). Figure 19 in the Appendix shows the actual annualized growth and level forecasts of the Canadian GDP using the monthly GDP and industrial production indicators respectively. Both indicators predict a downturn but the quarterly GDP is much more sensitive to movements in its monthly estimate. The scenario induced by the monthly GDP is much more pessimistic, especially in terms of persistence since the pre-Covid level of GDP is not reached even by the end of 2022. A similar pattern emerges for the Great Recession, see Figure 20 in the Appendix.

Figure 2: Actual forecasts of COVID recession and recovery: other indicators

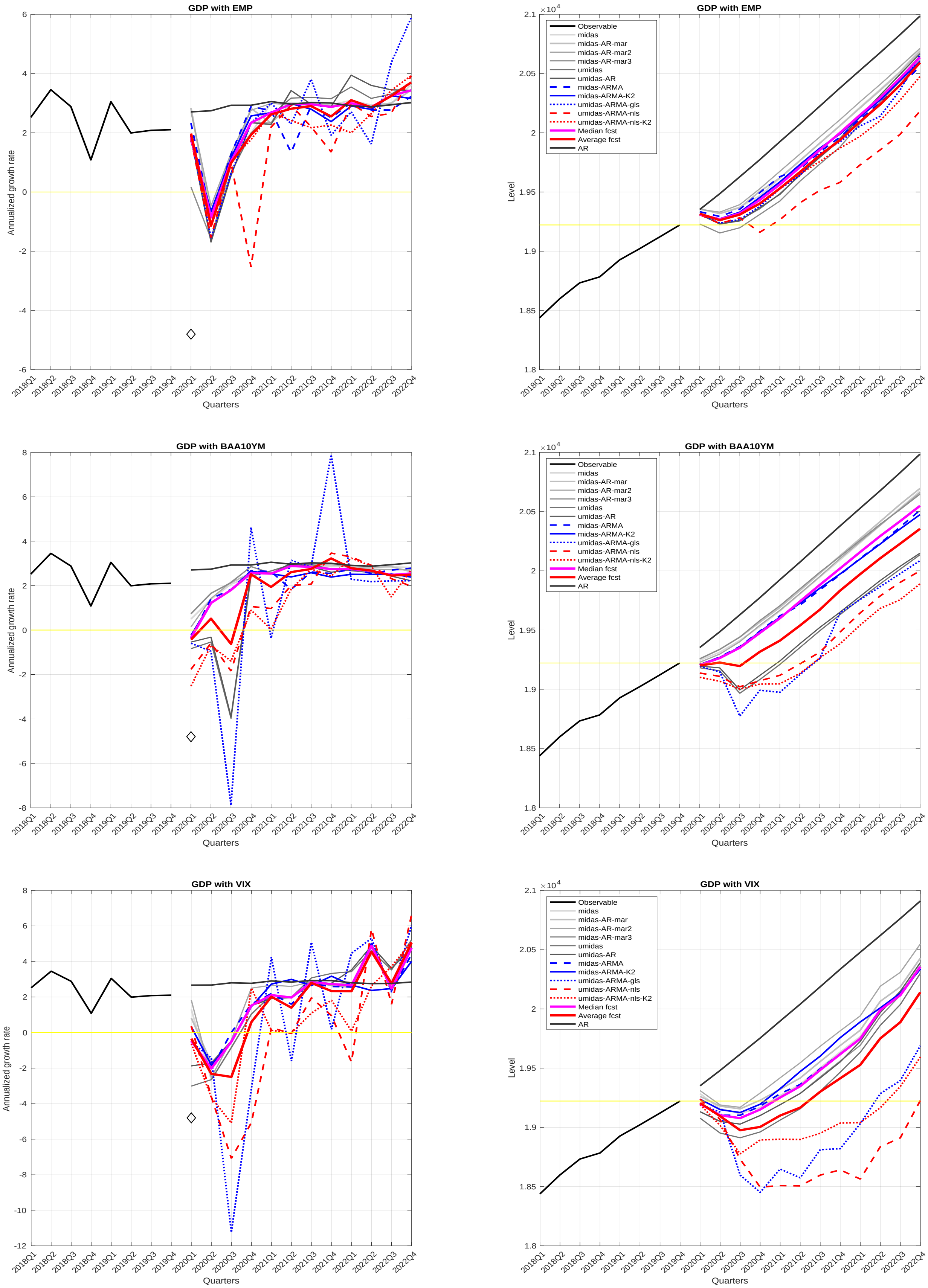


Figure 3: Actual forecasts of COVID recession and recovery: other indicators

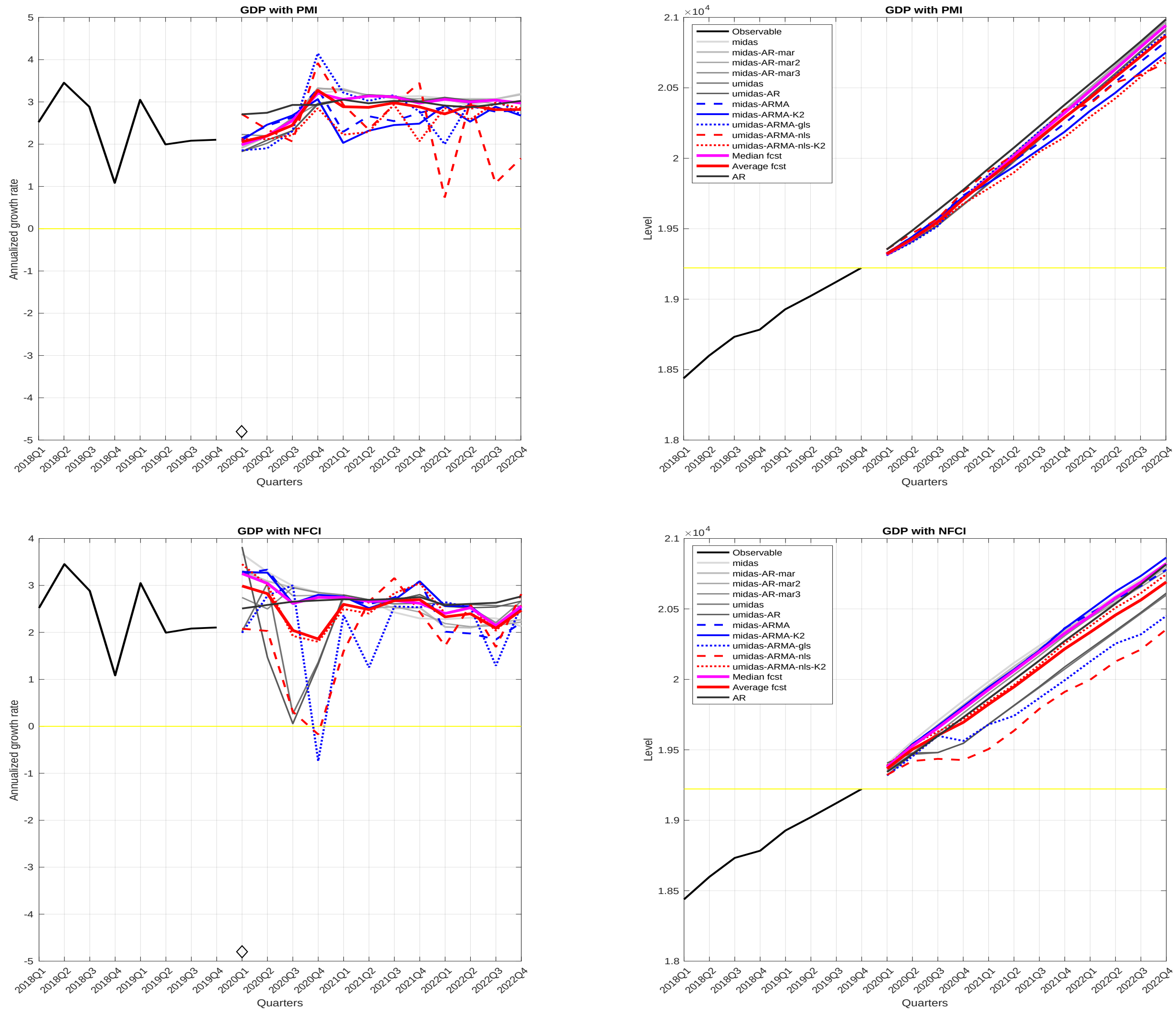
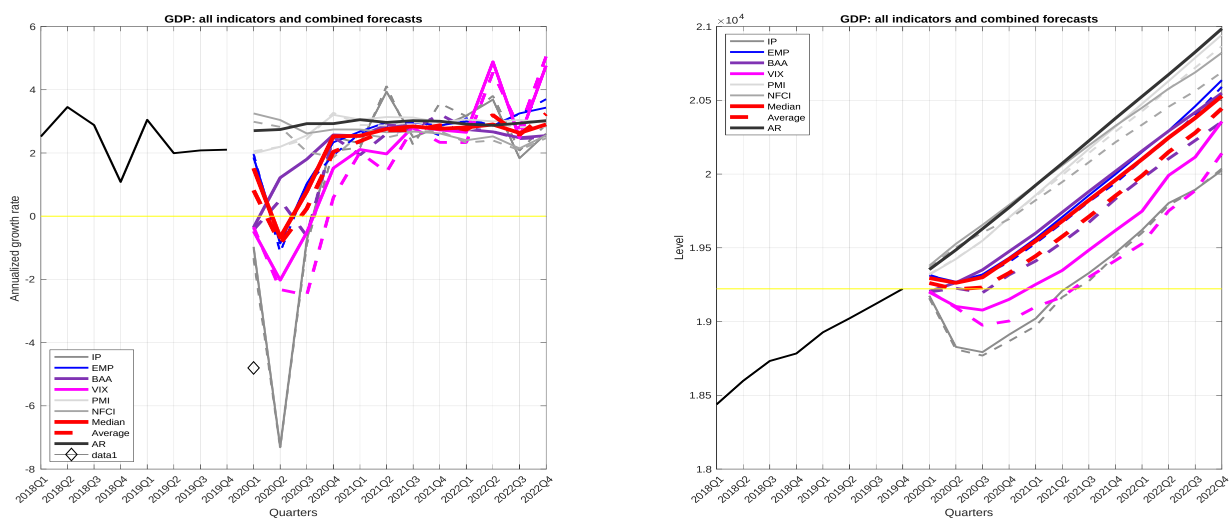


Figure 4: Actual forecasts of COVID recession and recovery: combined forecasts



tence of the pandemic shock and provide the most pessimistic recovery scenarios. As it was the case with US data, forecast combination helps to stabilize predictions, which seems especially helpful in the case of Italy and Japan where the model instability is more pronounced.

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 weights 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 this first subsection we assess the performance of the models during the financial crisis, and compare that to the Covid-19 period. In the second subsection we evaluate the Covid-19 adjustments.

5.1 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 included. Hence, it is the same situation in terms of monthly information available within the quarter to be nowcasted. Note that we use historical and not the 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, Figures 7 and 8 plot the out-of-sample growth and level nowcasts and forecasts. Table 3 reports the MSE and MAE for all models and all indicators, relative to an AR model, over the 2008Q3-2013Q2 period (hence across different forecast horizons). We do not present statistical tests for the significance of differences in MSE and MAE across models due to the short sample size that makes any test unreliable due to very low power. A few comments can be made. First, the actual value of GDP annualized growth for 2008Q3 was -2.17. Several models with IP as indicator returned even more negative nowcasts, while all the models with EMP as predictor returned (slightly) higher values. Second, the actual value for 2008Q4 was even more negative, and in this case even with IP as predictor all the forecasting models were a bit too optimistic, while the forecasts with EMP as indicator were substantially out of target. Third, IP predicted a faster recovery than realized, much more so EMP. Fourth, and in line with the outcome from Figures 7 and 8, according to Table 3, the best nowcasts and forecasts are produced by models with IP as indicator rather than EMP, the gains with respect to the AR model are substantial, and the best specifications are UMIDAS and UMIDAS-AR, with relative MSE of 0.62 and 0.63, respectively. Fifth, including an MA term does not help, actually it leads

Figure 5: Actual forecasts of COVID recession and recovery: Rest of G7

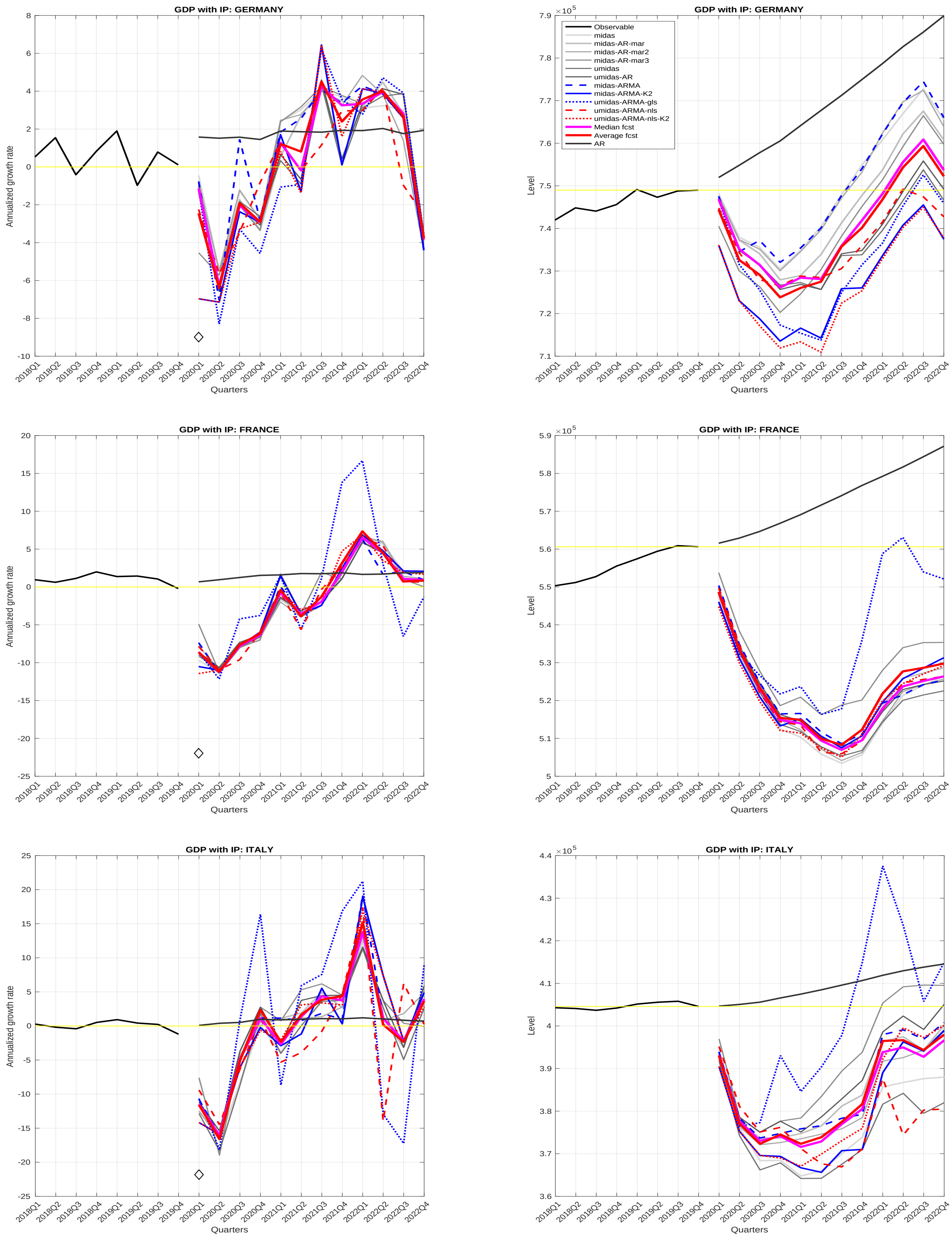
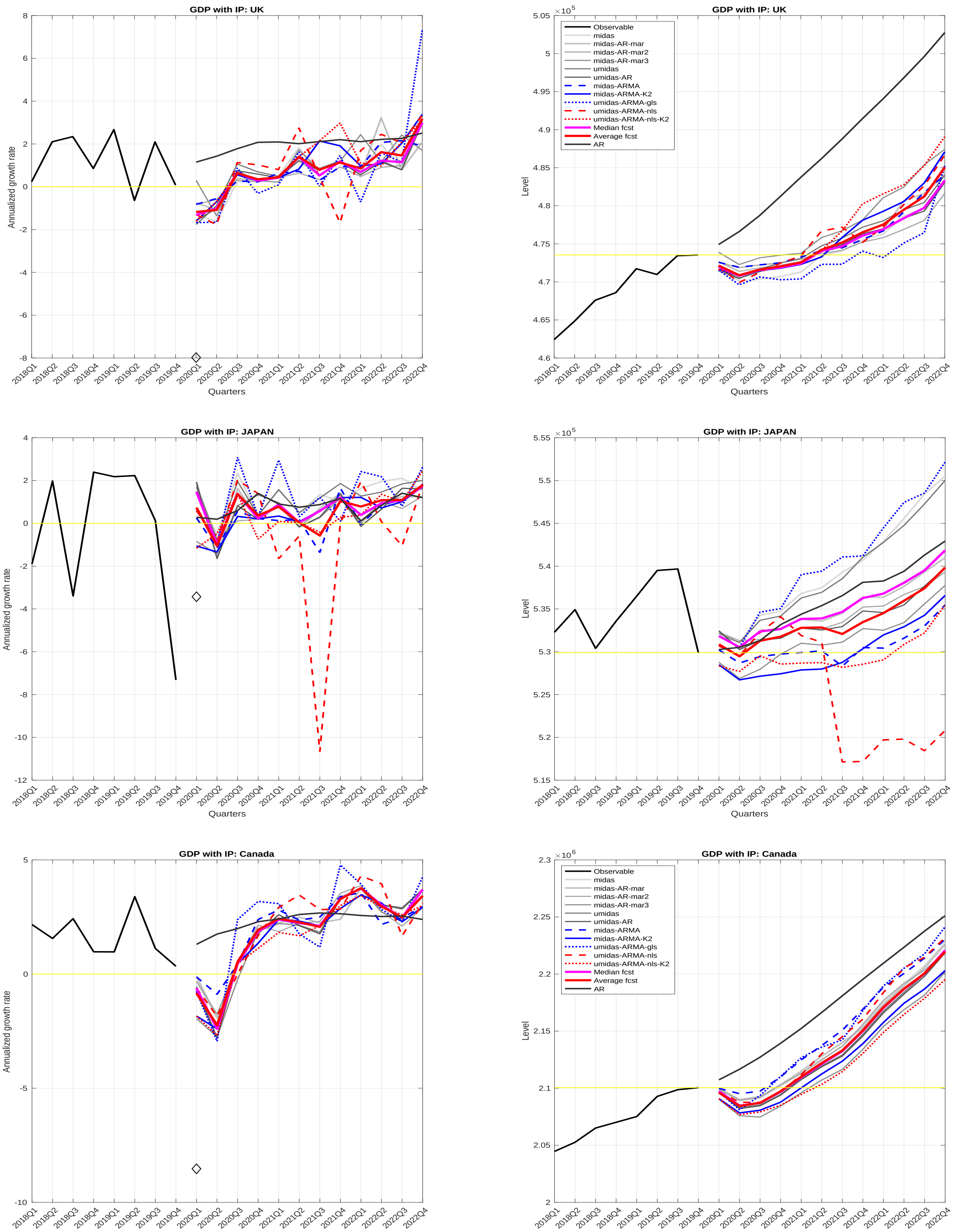


Figure 6: Actual forecasts of COVID recession and recovery: Rest of G7, cont.



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 MSE.

Moving to the other G7 countries, Figures 9 and 10 present results for both growth and level of GDP based on IP only. The depth of the recession was systematically underestimated, less so for France and much more so for Japan. For France, and partly for Germany, forecasts for the recovery period were rather accurate, while they were way too optimistic for Italy, Japan, UK and Canada. Table 4 compares the RMSE and MAE of the various models with respect to an AR specification. The table clearly indicates that the mixed-frequency approach brings the biggest improvements to predict GDP growth for France, Italy, Canada and the UK. In terms of best models, umidas is generally the most resilient, with the lowest RMSE and MAE for France and Canada, while midas-AR-mar2 is the most accurate for Italy. Adding MA terms in general does not improve the results, while combining forecast is generally the second-best alternative.

To conclude, while monthly information, in our case data on IP, improves substantially 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. And a 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 their 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 be really comparable). However, in the next subsection we implement these approaches to modify the 2020Q1 nowcasts and see whether the precision increases with respect to that obtained from the standard models of the previous section.

5.2 Adjusting Covid-19 recession and recovery forecasts

Figures 11 and 12 compare the GDP growth and level forecasts for the US from Figure 1 with predictions adjusted by intercept correction or similarity based estimation. We focus on average forecasts (in bold), with results for other models dashed lines. More specifically, the intercept corrected nowcasts and forecasts are obtained for each model and indicator by adding to the unadjusted values in Figure 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.

Figure 7: Out-of-sample forecasts of Great Recession and recovery: US

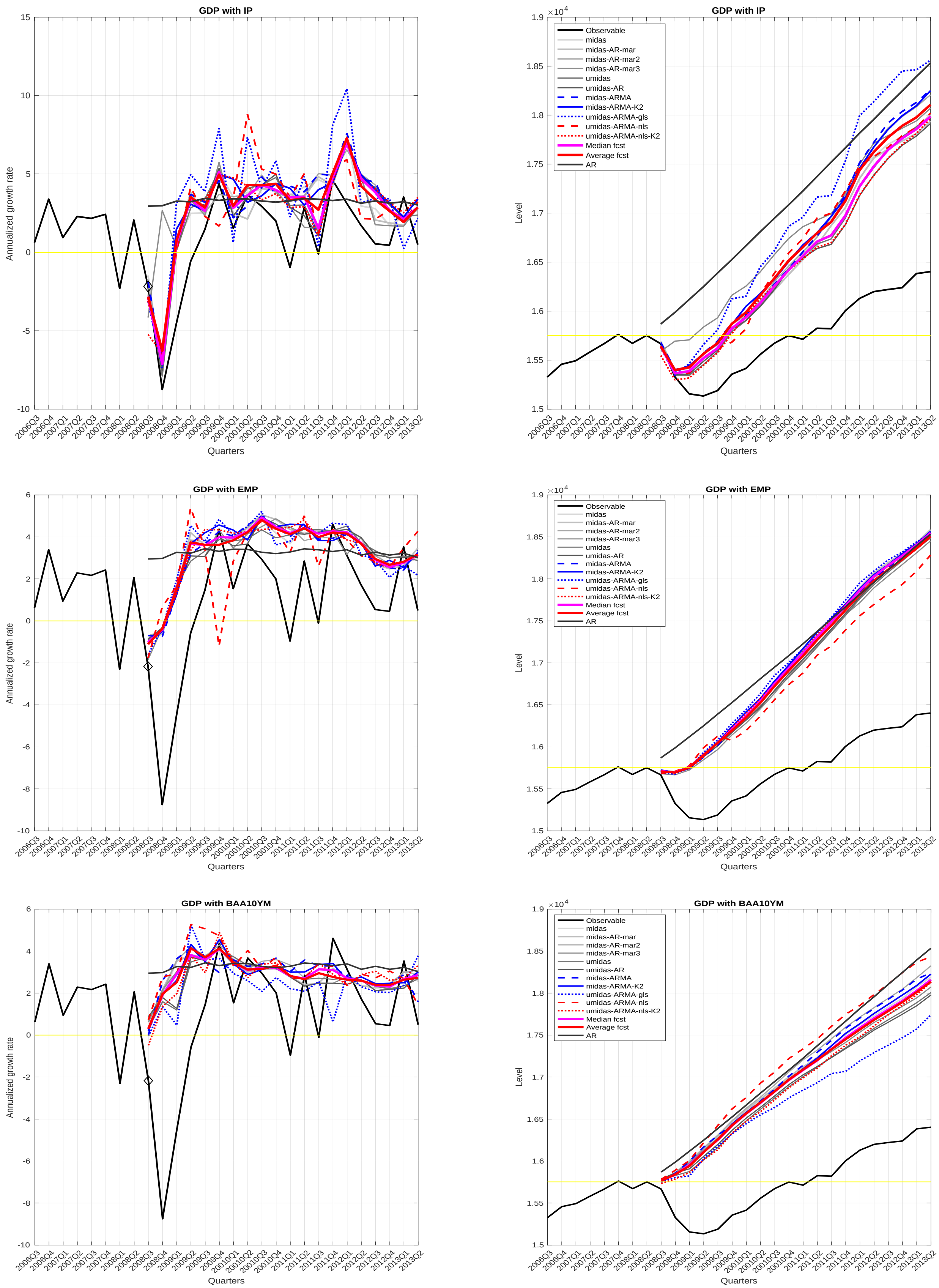


Figure 8: Out-of-sample forecasts of Great Recession and recovery: US, cont.

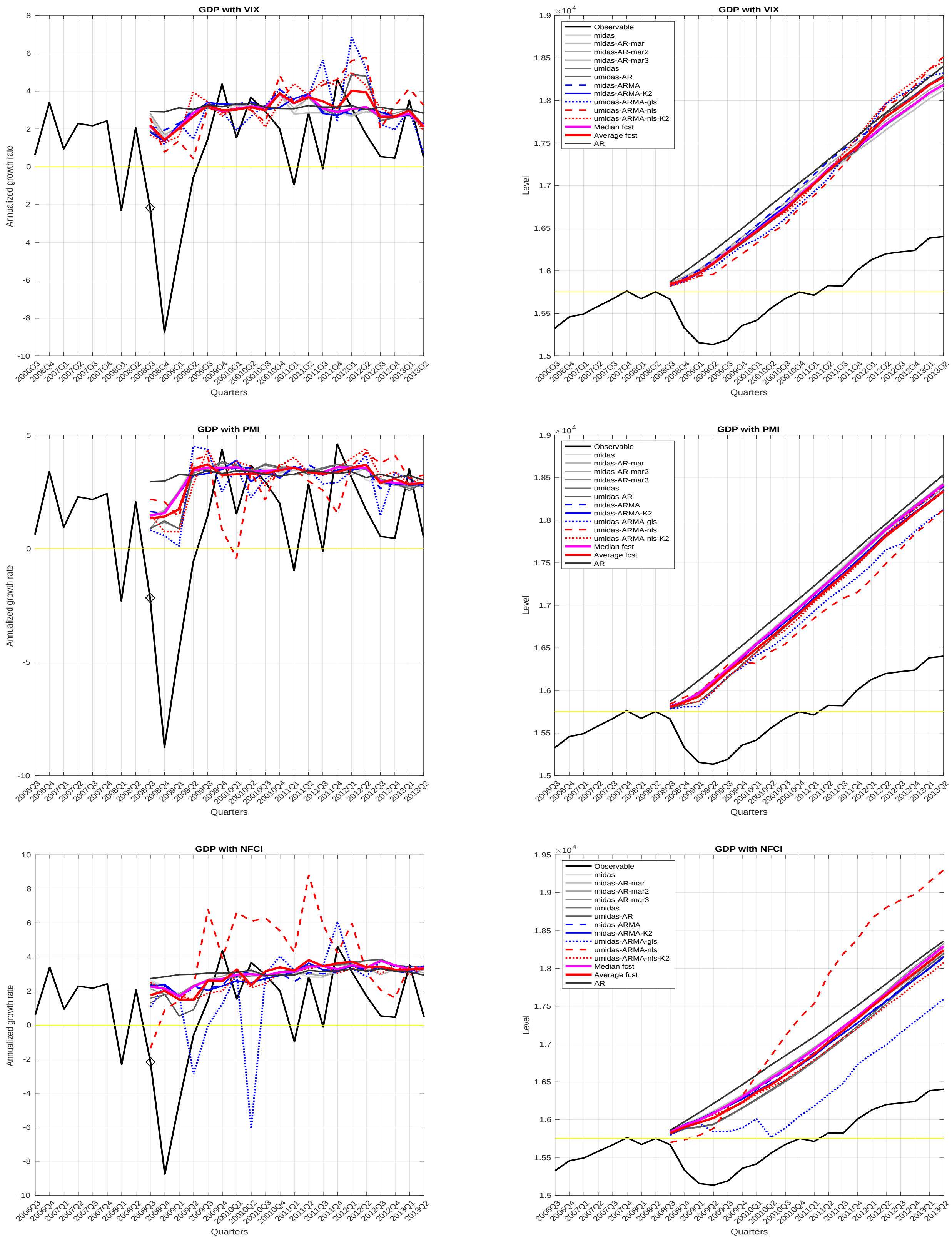


Table 3: Relative predictive accuracy: US with all indicators

	IP		EMP		BAA10Y	
Models	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

	VIX		PMI		NFCI	
Models	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 MSE and MAE based on 2008Q3-2013Q2 period (hence across different forecast horizons).

Table 4: Relative predictive accuracy: Rest of G7

	DE		FR		IT	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
AR	5.63	3.38	2.91	2.26	4.79	3.34
midas	0.98	1.18	0.77	0.85	0.76	0.89
midas-AR-mar	0.96	1.12	0.69	0.69	0.76	0.91
midas-AR-mar2	1.00	1.21	0.71	0.78	**0.61**	**0.69**
midas-AR-mar3	0.99	1.17	0.86	0.88	0.90	0.93
umidas	0.98	1.06	**0.63**	**0.66**	0.84	0.90
umidas-AR	**0.95**	**1.05**	0.82	0.84	0.84	0.88
midas-ARMA	1.05	1.20	0.65	0.72	0.67	0.78
midas-ARMA-K2	1.00	1.22	0.67	0.67	0.76	0.82
umidas-ARMA-gls	0.96	1.02	0.74	0.73	0.85	0.98
umidas-ARMA-nls	1.18	1.43	0.75	0.82	0.86	0.93
umidas-ARMA-nls-K2	0.99	1.09	0.69	0.71	0.86	0.89
Median fcst	0.96	1.11	0.67	0.71	0.76	0.86
Average fcst	0.96	1.05	0.66	0.70	0.73	0.82
	UK		JP		CA	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
AR	3.24	2.57	6.85	5.27	3.85	2.46
midas	0.86	0.88	0.96	0.95	0.68	0.85
midas-AR-mar	0.91	0.94	0.97	0.97	0.67	0.84
midas-AR-mar2	**0.79**	0.84	**0.96**	0.96	0.72	0.87
midas-AR-mar3	1.00	1.03	0.96	0.96	0.98	1.01
umidas	0.82	**0.81**	1.00	**0.94**	**0.60**	**0.76**
umidas-AR	0.89	0.94	1.00	0.96	0.61	0.77
midas-ARMA	0.99	1.07	1.00	1.04	0.70	0.90
midas-ARMA-K2	0.89	0.96	0.99	1.00	0.79	1.00
umidas-ARMA-gls	0.89	0.86	0.96	0.97	0.73	0.90
umidas-ARMA-nls	1.06	1.02	0.96	0.95	0.79	0.84
umidas-ARMA-nls-K2	0.95	1.04	0.99	1.00	0.82	0.99
Median fcst	0.82	0.87	0.96	0.96	0.67	0.81
Average fcst	0.82	0.89	0.97	0.97	0.70	0.85

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

Figure 9: Out-of-sample forecasts of Great Recession and recovery: Rest of G7

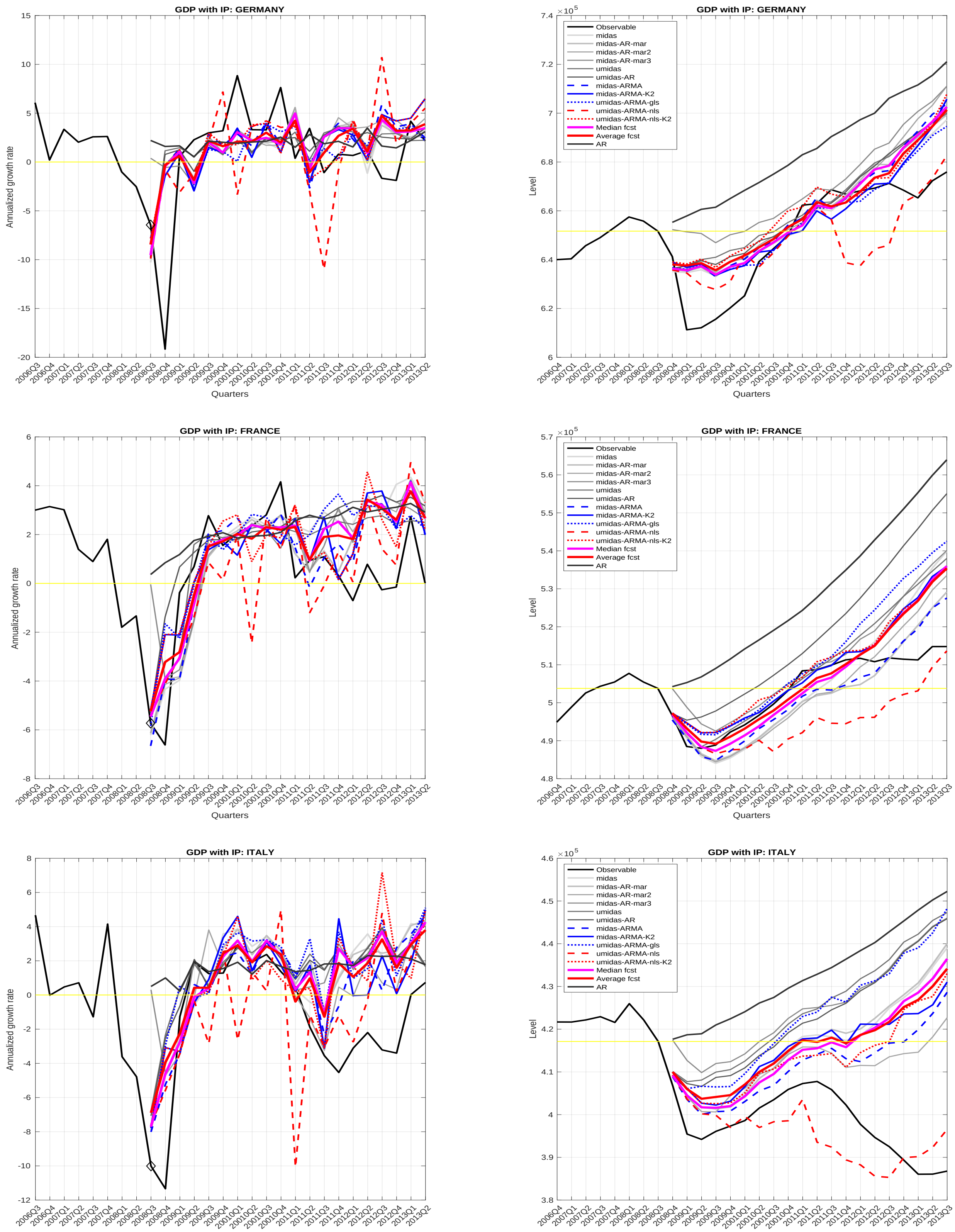
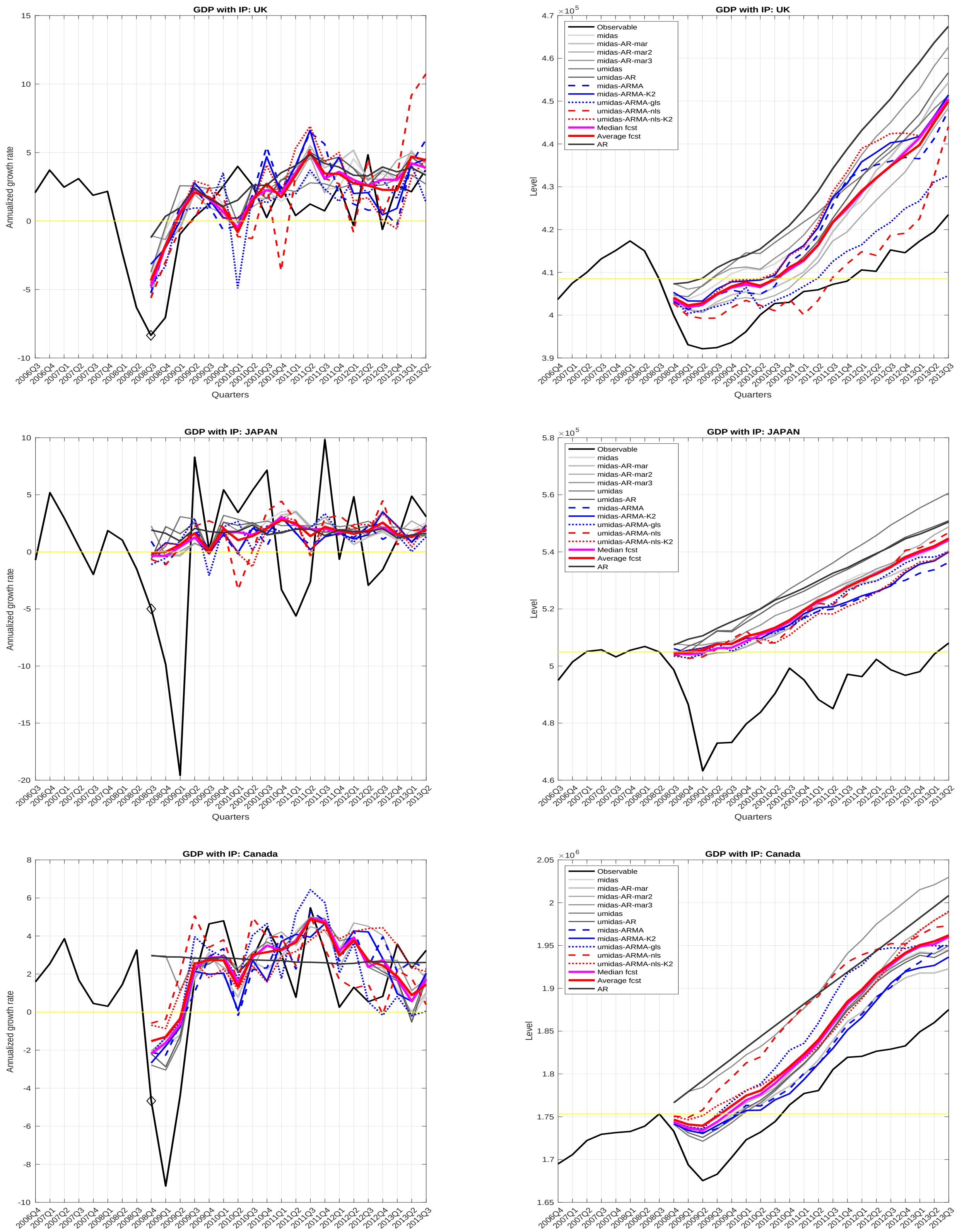


Figure 10: Out-of-sample forecasts of Great Recession and recovery: Rest of G7



The figures highlight that similarity estimation has overall limited effects on the nowcasts and forecasts, while the differences are substantial with intercept correction. In case of 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, more so when employment is used as a predictor. As a consequence, there are even larger differences between corrected and uncorrected forecasts for GDP level, with the former suggesting that the pre-Covid-19 level could 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. This suggests that the role of these variables changes during crisis time, and estimation over shorter periods dominated by the crisis event makes them more important, improving the nowcasts and forecasts during similar subsequent crisis moments.

Another interesting effect of the correction is to make all the nowcasts and forecasts much more similar among themselves. A principal component analysis of the standard and intercept corrected alternative nowcasts and forecasts across all predictors and models, shown in Figure 13, 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 get shrunk after the adjustment.

It is also worth mentioning that, due to the direct forecasting approach and the need to estimate some nonlinear (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 the 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 predictor, see Table 5.

In Figures 14 and 15 we report the results for the other G7 countries. Similarity adjustment brings the nowcast of 2020Q1 very close to its first release for Germany and Japan, while the intercept correction improves the nowcast for Italy, UK and Canada. As for the US, the most relevant adjustment for the subsequent forecast periods comes from the intercept correction, except for France (where the forecast errors during the financial crisis and recovery period were comparably low). In particular, the similarity approach suggests a very pessimistic path for Italy. This is because in Italy the recovery after the financial crisis was particularly problematic, and unfortunately the same can be expected during the post-Covid-19 period but it is not captured by the standard models.

Figure 11: Adjusted forecasts of COVID recession and recovery

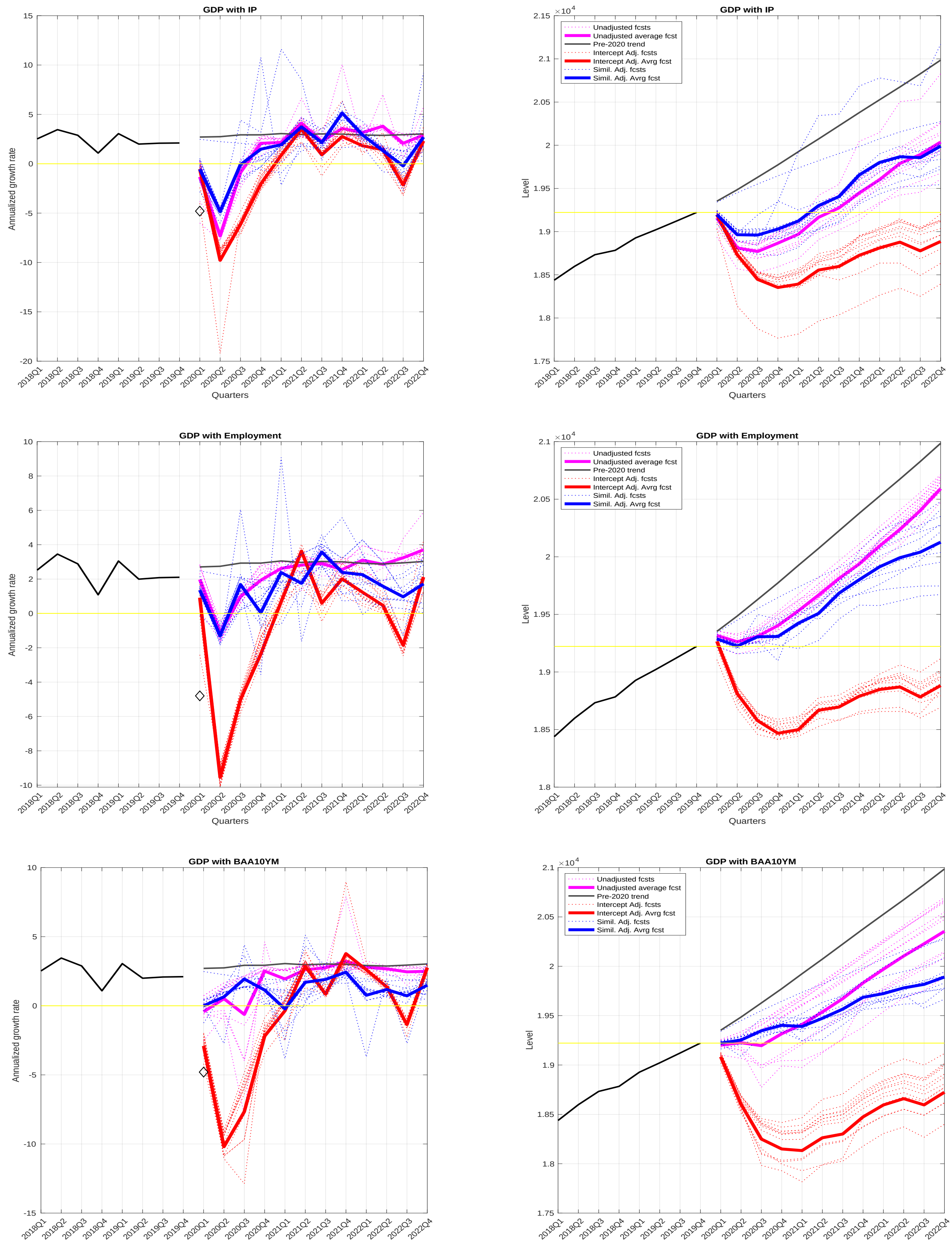


Figure 12: Adjusted forecasts of COVID recession and recovery, cont.

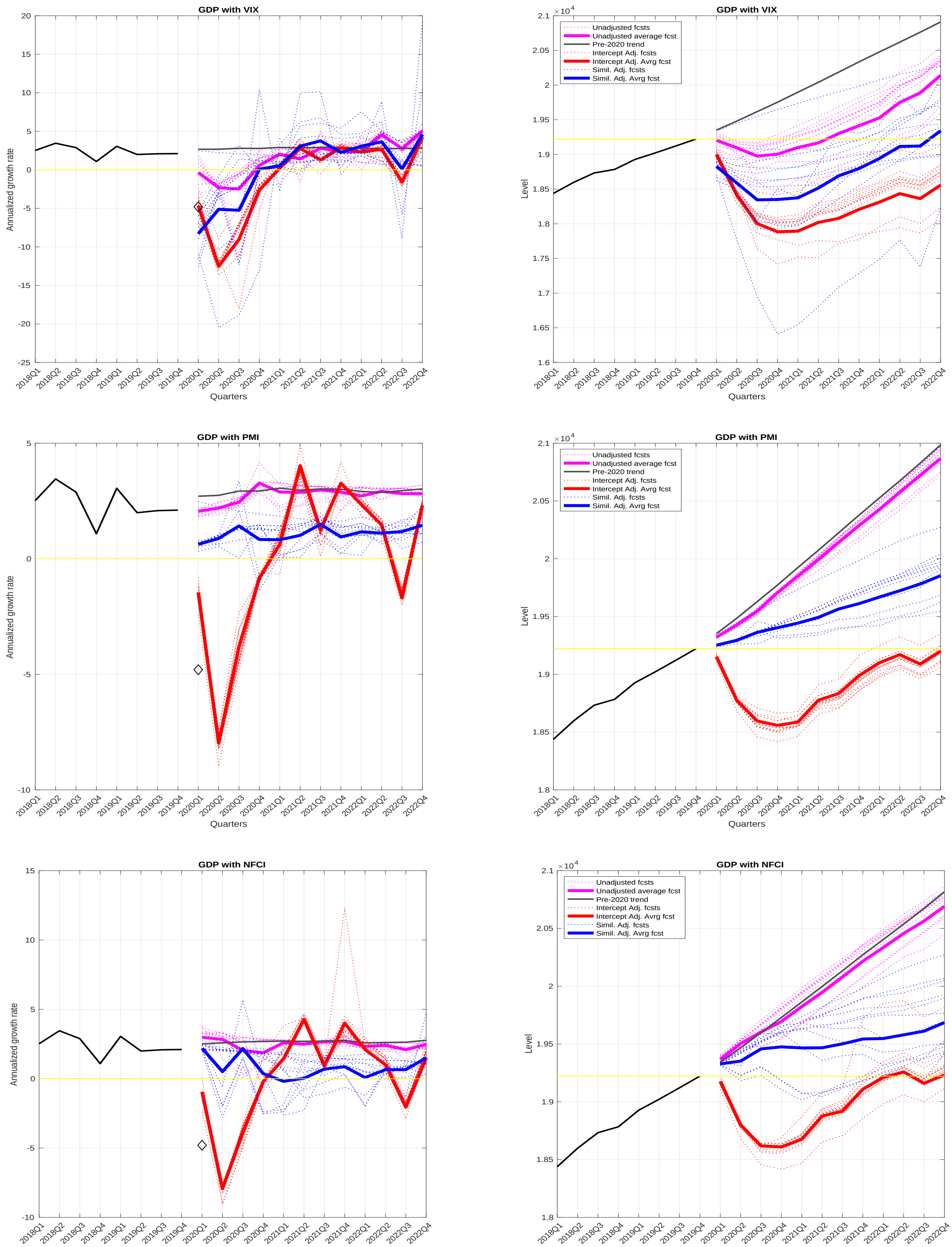


Figure 13: Factor structure of unadjusted and adjusted forecasts

(a) All forecasts

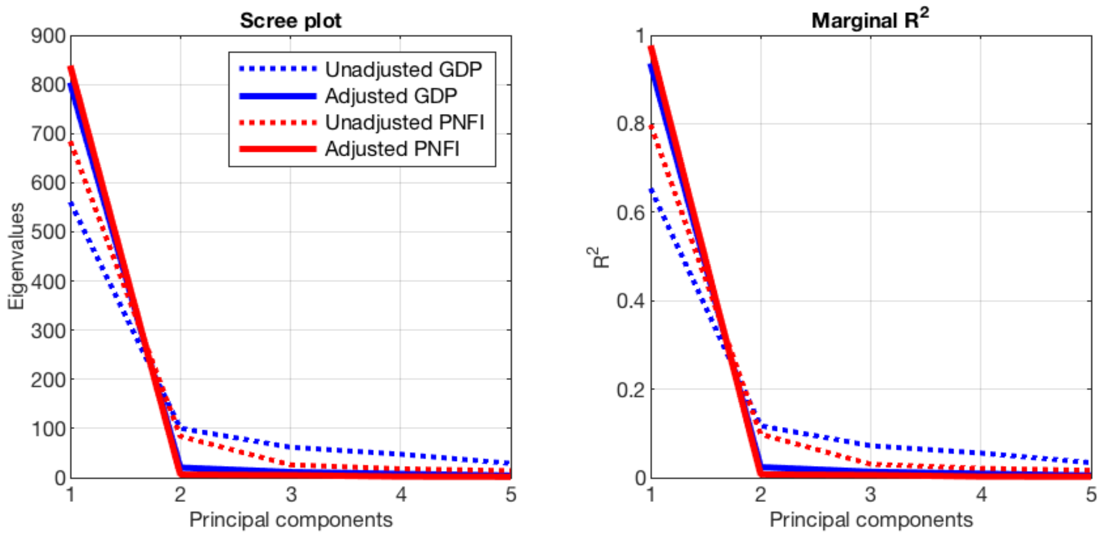


Table 5: Nowcasting 2020Q1 US GDP

	IP	EMP	BAA10Y	VIX	PMI	NFCI
Unadjusted average fcst	-1.33	1.98	-0.43	-0.34	2.06	2.99
Intercept Adj. Avrg fcst	-0.54	0.91	-2.91	-4.66	-1.45	-0.94
Similarity Adj. Avrg 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 have been estimated on 2008Q1 - 2011Q3 window.

Figure 14: Adjusted forecasts of COVID recession and recovery: rest of G7

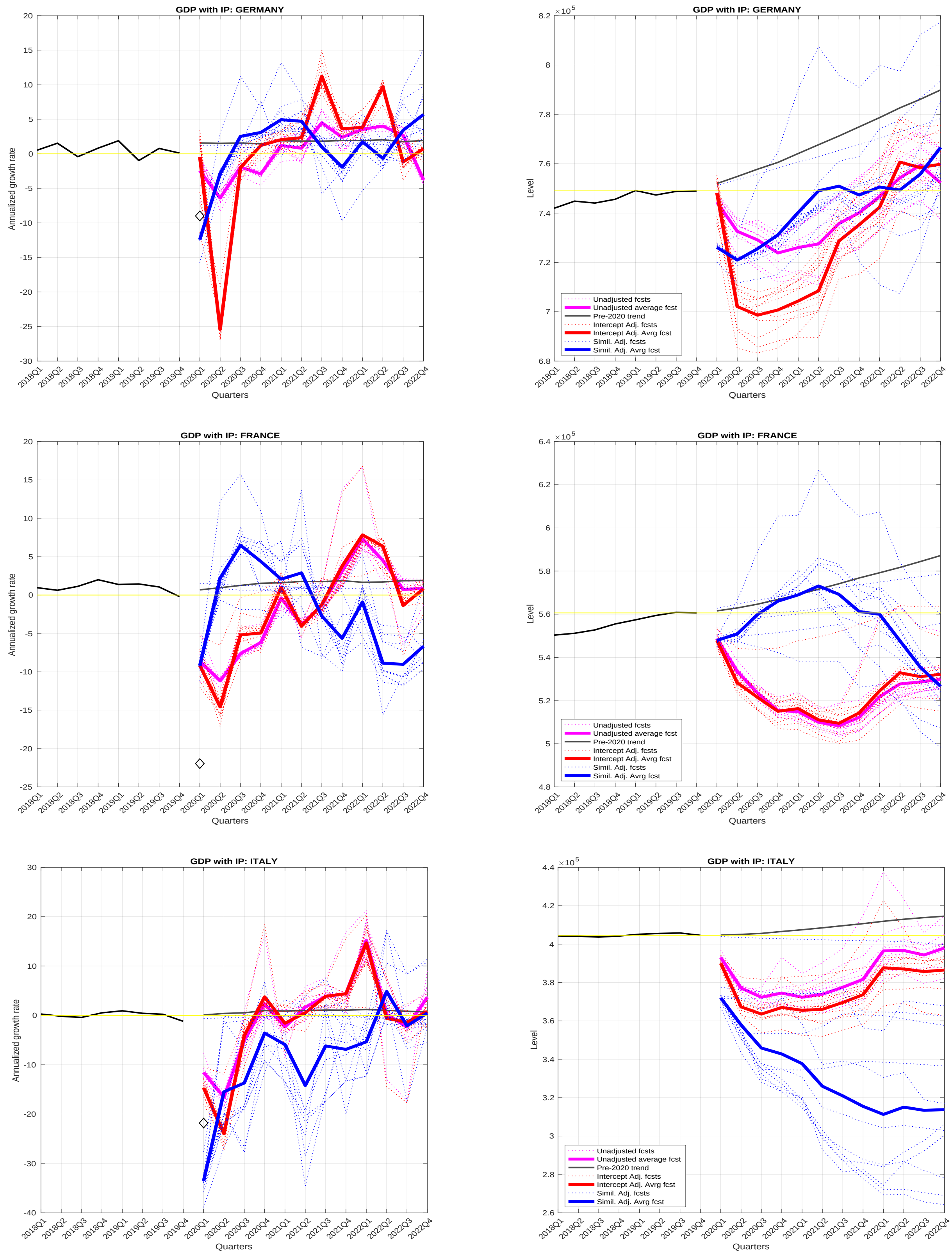


Figure 15: Adjusted forecasts of COVID recession and recovery: rest of G7, cont.

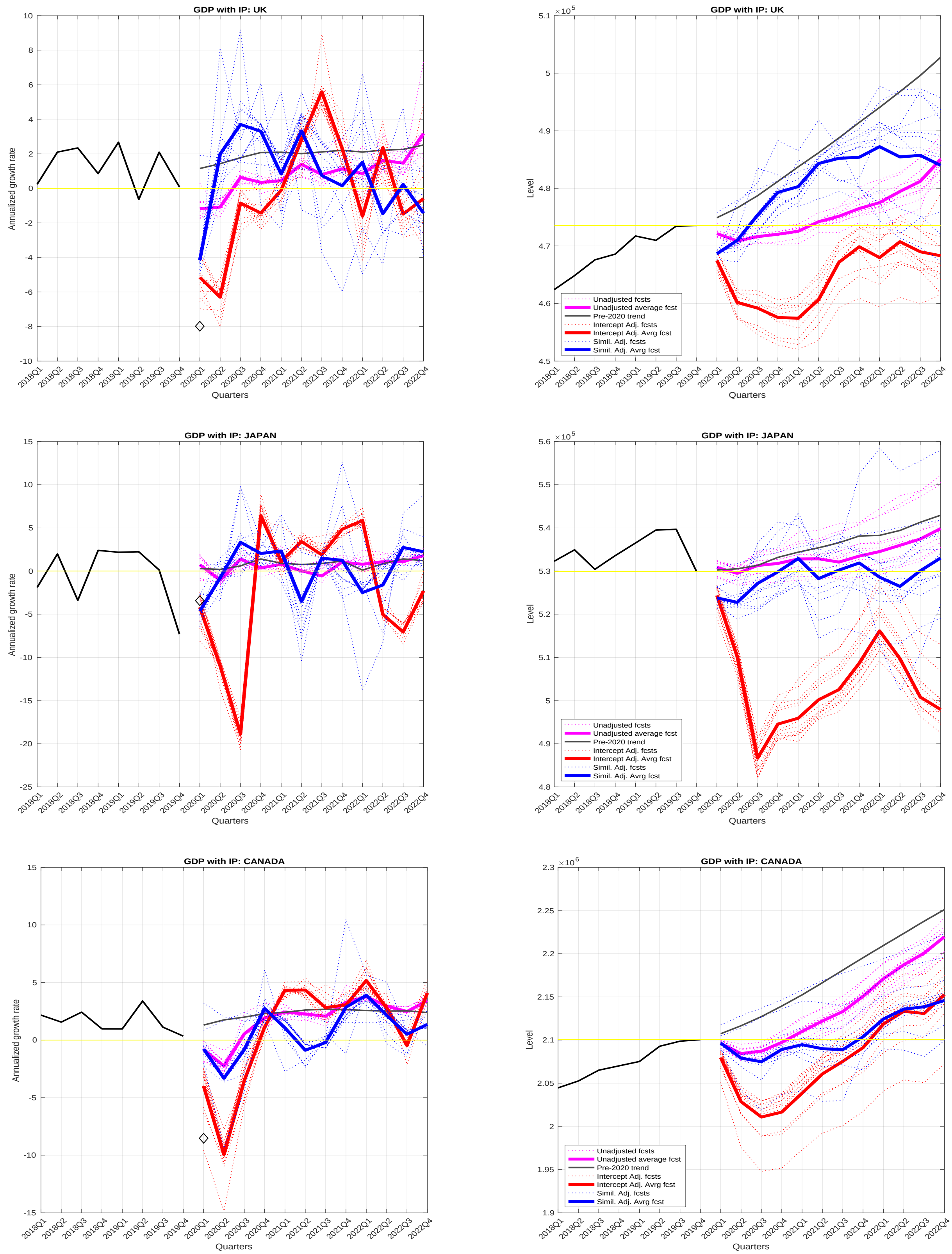
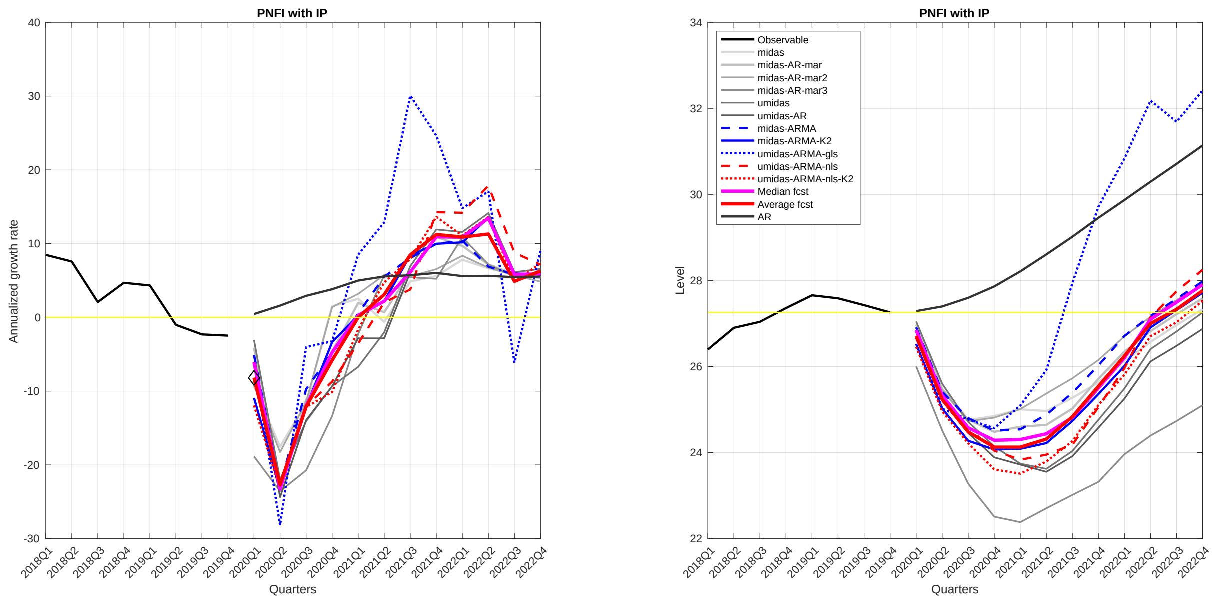


Figure 16: Actual forecasts of COVID recession and recovery: US investment



6 Predicting the Covid-19 effects on investment

As business cycle fluctuations are typically driven by those in private investment, we now assess normal and adjusted Covid-19 nowcasts and forecasts for the US real private nonresidential fixed investment (PNFI). Figure 16 plots the PNFI nowcasts and forecasts using all the models in Table 1 and IP as predictor. Again, the left panel shows the annualized growth rate, and the level forecasts are in the right panel.

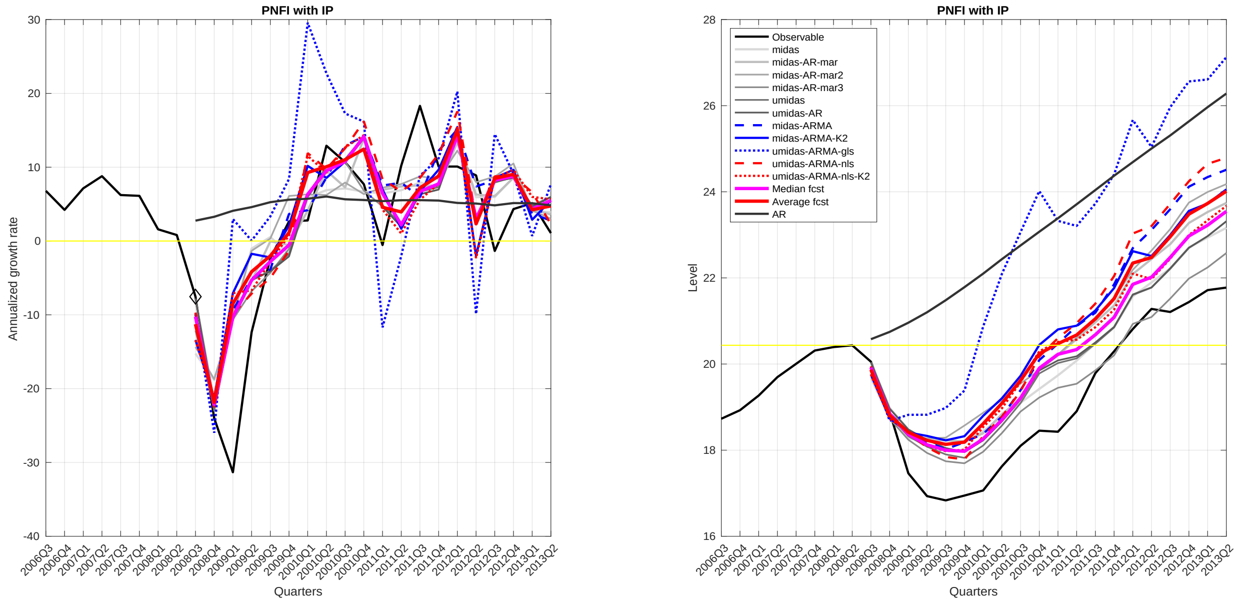
All models predict an important decrease of the US investment growth in the first quarter of 2020. The most pessimistic is midas-AR-mar3 with a nowcast of -18%, followed by MA alternatives such as umidas-ARMA-nls-K2 and midas-ARMA-K2 that suggest -12% and -11% respectively. These values turn out to be 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 the pre-Covid PNFI level 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 a strong recovery already in 2021.

Figures 21 and 22, 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 indicator, 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

Figure 17: Out-of-sample forecasts of Great Recession and recovery: US investment

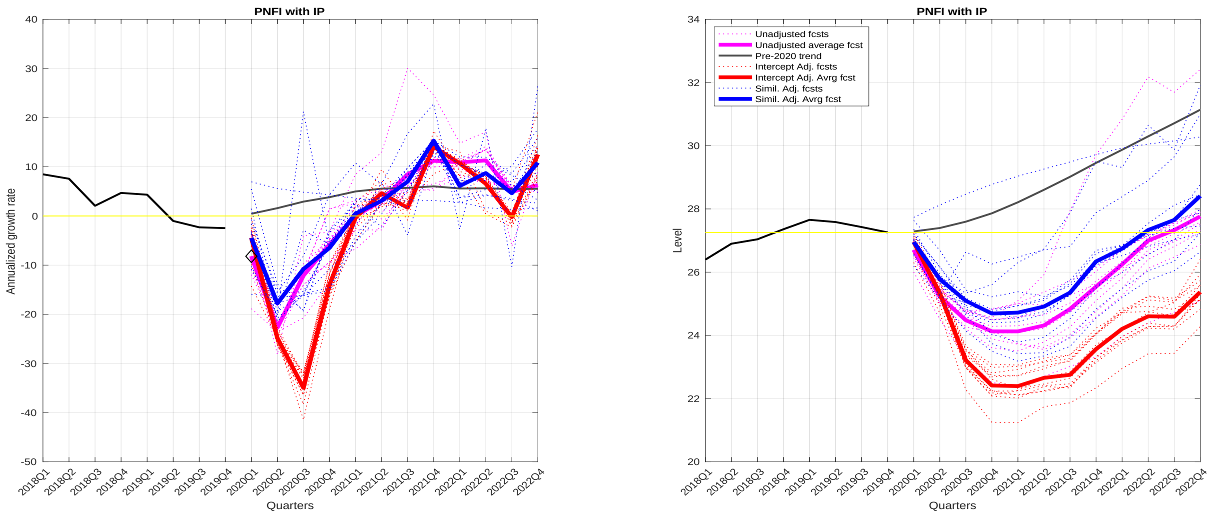


same as with GDP: the forecasting period is 2008Q3 - 2013Q2, while PNFI and predictors are supposed observable until 2008Q2 and 2008M09 respectively. Figure 17 shows the out-of-sample growth and level nowcasts and forecasts using IP as indicator. The real PNFI has decreased by -7.4% in 2008Q3 and all models returned even more negative nowcasts. But, they all failed to predict the huge drop in 2009Q1 and hence suggested a too optimistic recovery. The performance of all other predictors is reported in Figures 23 - 24, in the Appendix. Using employment and credit spread produced quite accurate nowcasts for 2008Q3 period, but all models remained too optimistic for the rest of the recession and the subsequent recovery.

Table 6, in the Appendix, summarizes the performance of models and all predictors in terms of 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 is 0.54, MAE 0.57). As it was the case with GDP, combining forecasts is often the second-best option, while the MA adjustment is only sometimes beneficial.

Figure 18 compares the intercept and similarity adjusted nowcasts and forecasts to the unadjusted ones in figure 16. 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 the 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 level of investment. Figures 25 and 26, in the Appendix, report the results for all other predictors. The story is similar when employment is used, while the intercept adjustment corrects successfully the 2020Q1 nowcast provided by the credit spread. Both corrections do well in terms of nowcasting with VIX.

Figure 18: Adjusted forecasts of COVID recession and recovery: US investment



7 Conclusions

In this paper we assess simple methods to improve the 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 by a specific form of intercept correction.

Among all 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 following 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 in terms of bias of the unadjusted Covid-19 growth nowcasts and forecasts, and ranking and effects of the various adjustments methods, also emerge for the other G7 countries, with some interesting cross-country differences such as the expected faster recovery in Germany and slower in France, Italy and the UK.

The results are also similar for US private investment, a main driver of business cycle fluctuations. IP turns out to be most reliable indicator, given our timing, and intercept adjustment produces a precise nowcast for 2020Q1 and lowers 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 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 conclusions 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.

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A Additional results

A.1 Using monthly GDP instead of industrial production

Figure 19: COVID forecasts in Canada: monthly GDP versus industrial production

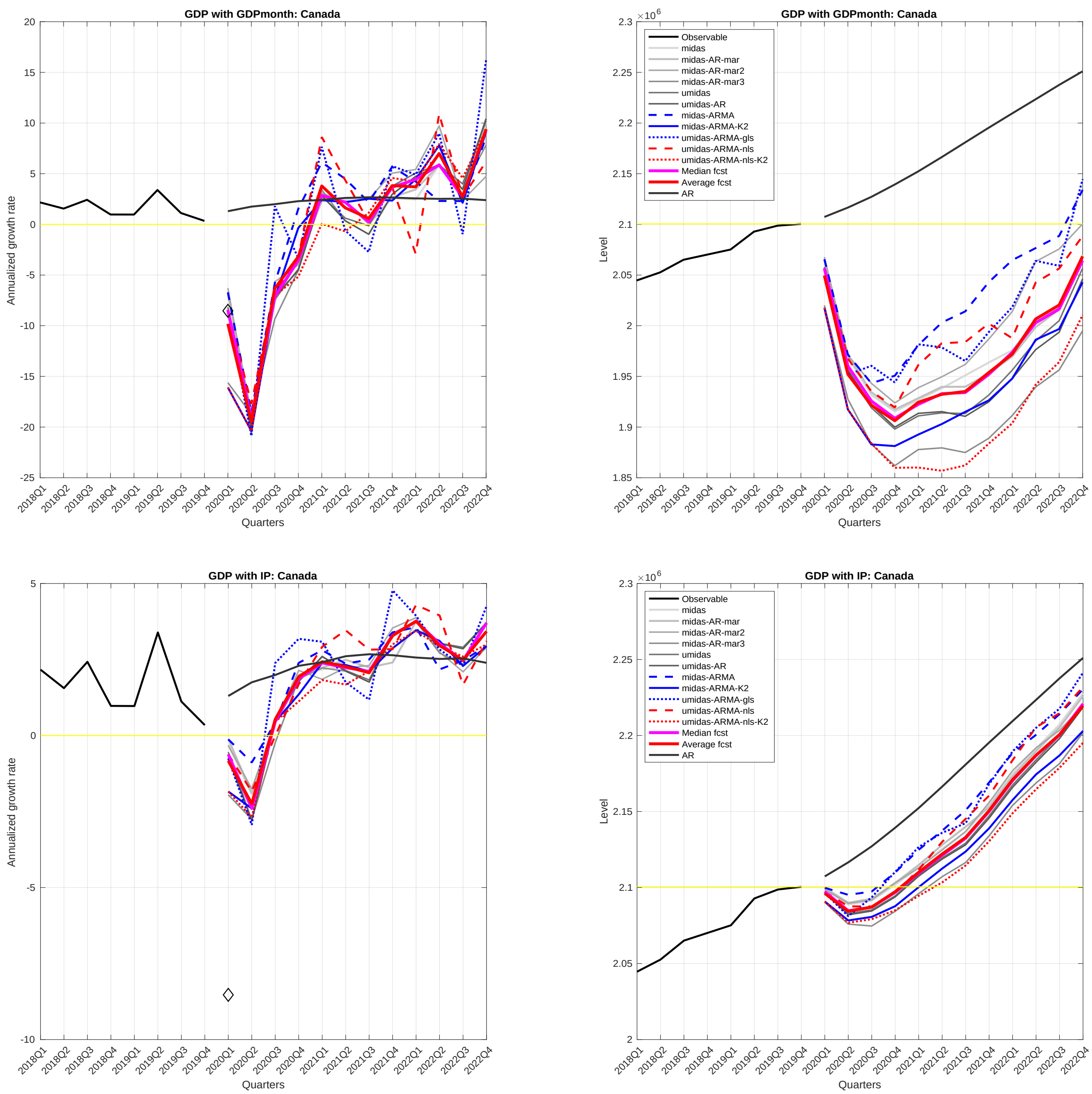
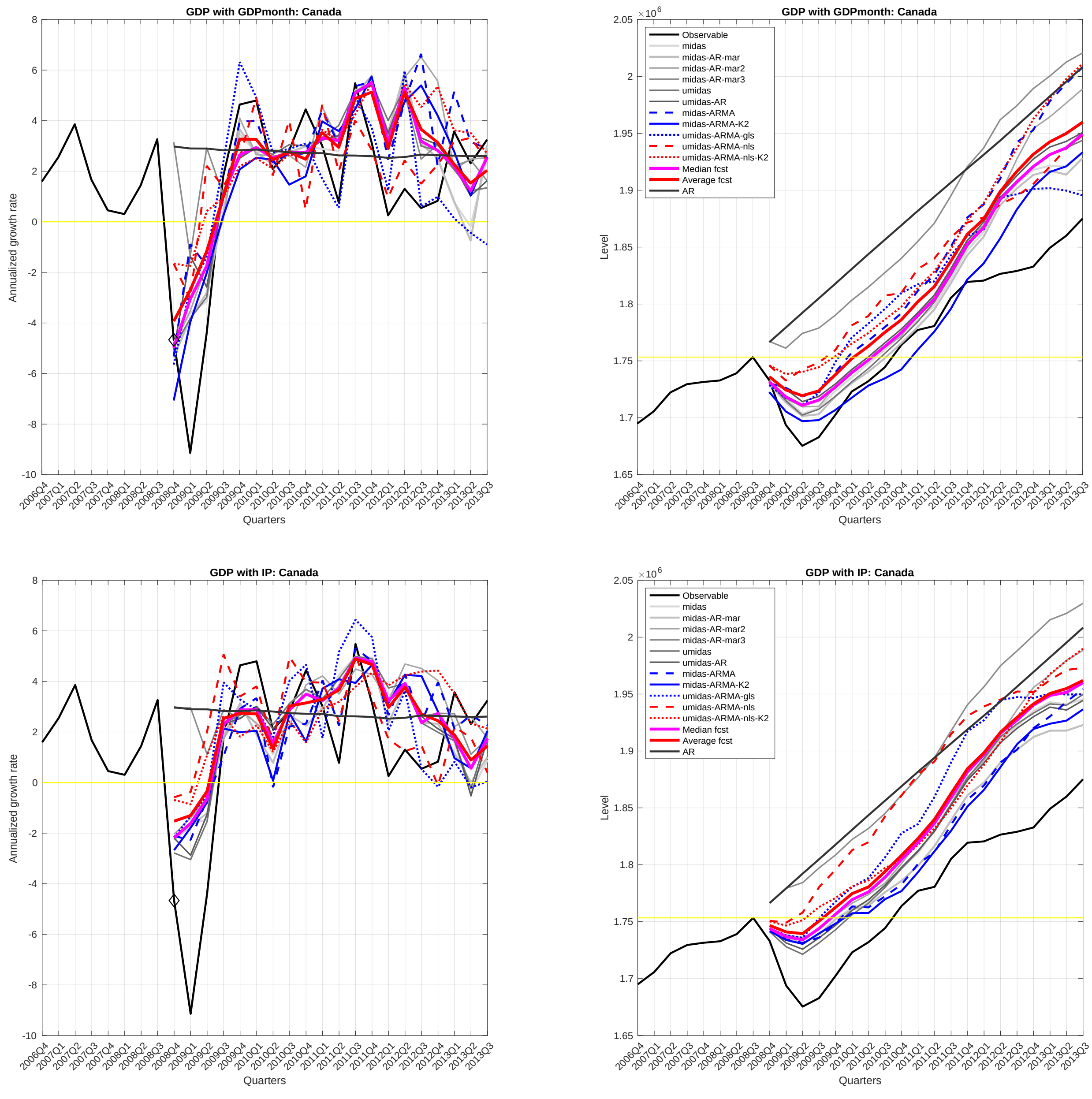


Figure 20: Forecasts of Great Recession in Canada: monthly GDP versus industrial production



A.2 Forecasting US investment

Figure 21: Actual forecasts of COVID recession and recovery: other indicators

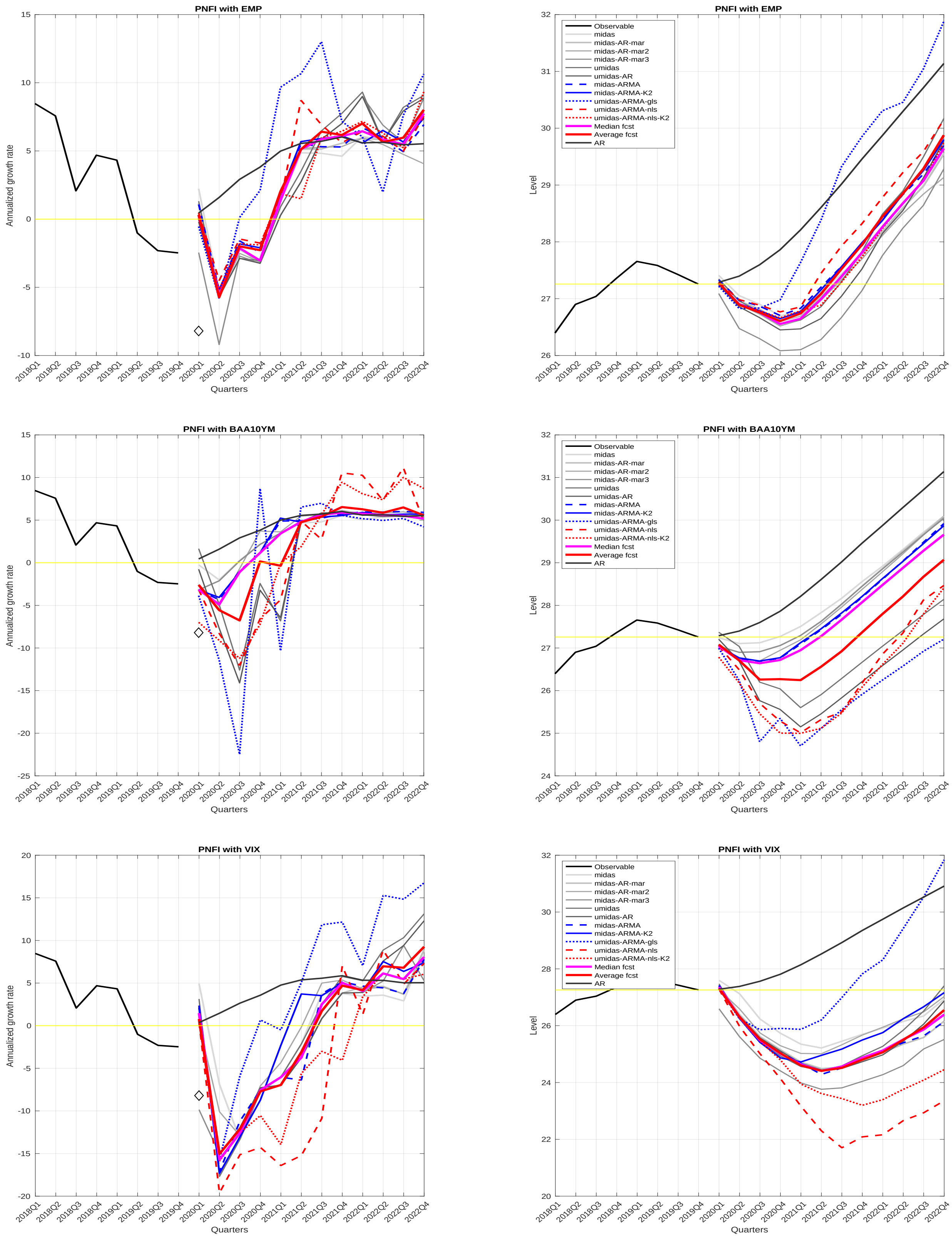


Figure 22: Actual forecasts of COVID recession and recovery: other indicators

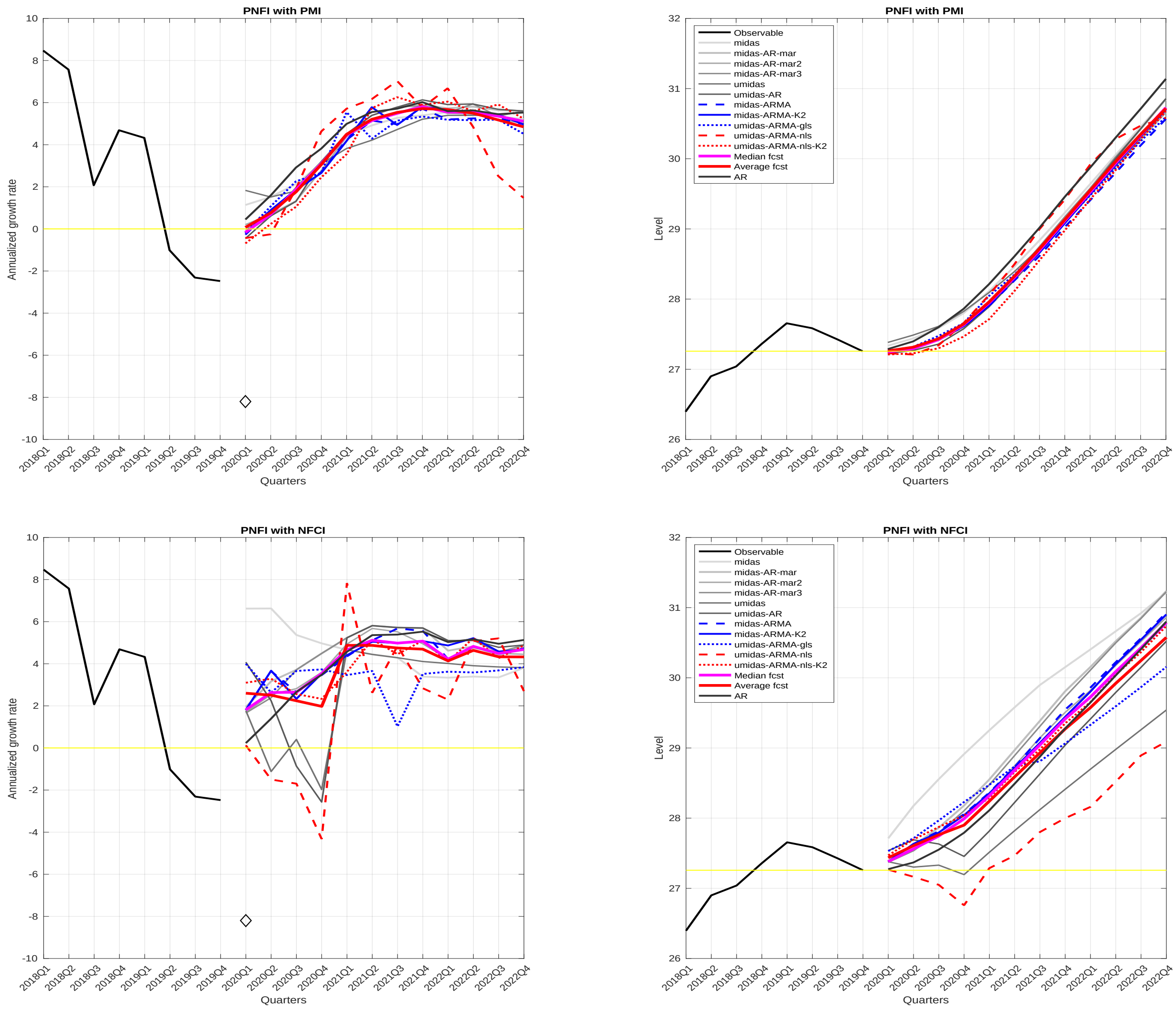


Figure 23: Out-of-sample forecasts of Great Recession and recovery: US investment

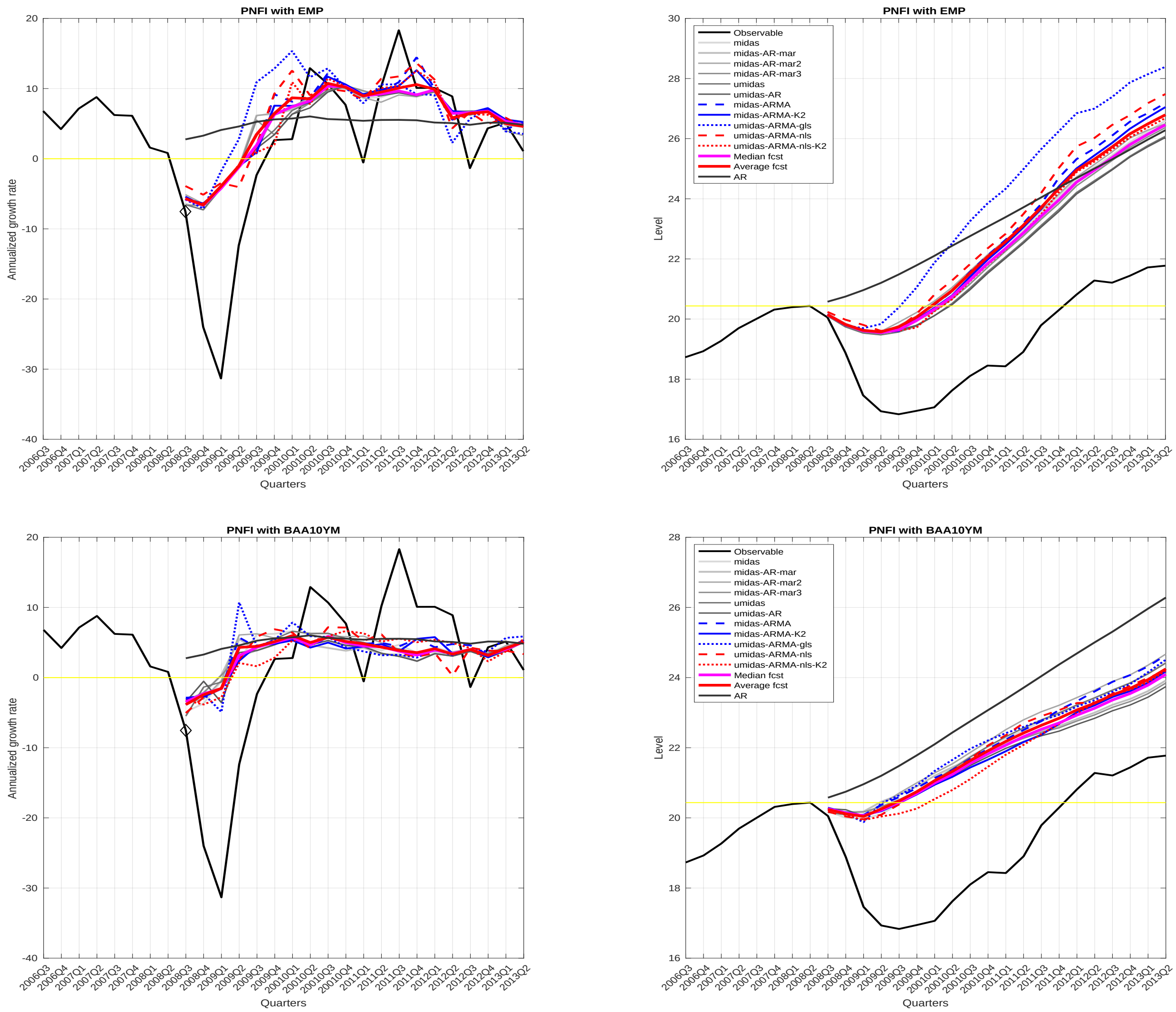


Figure 24: Out-of-sample forecasts of Great Recession and recovery: US investment, cont.

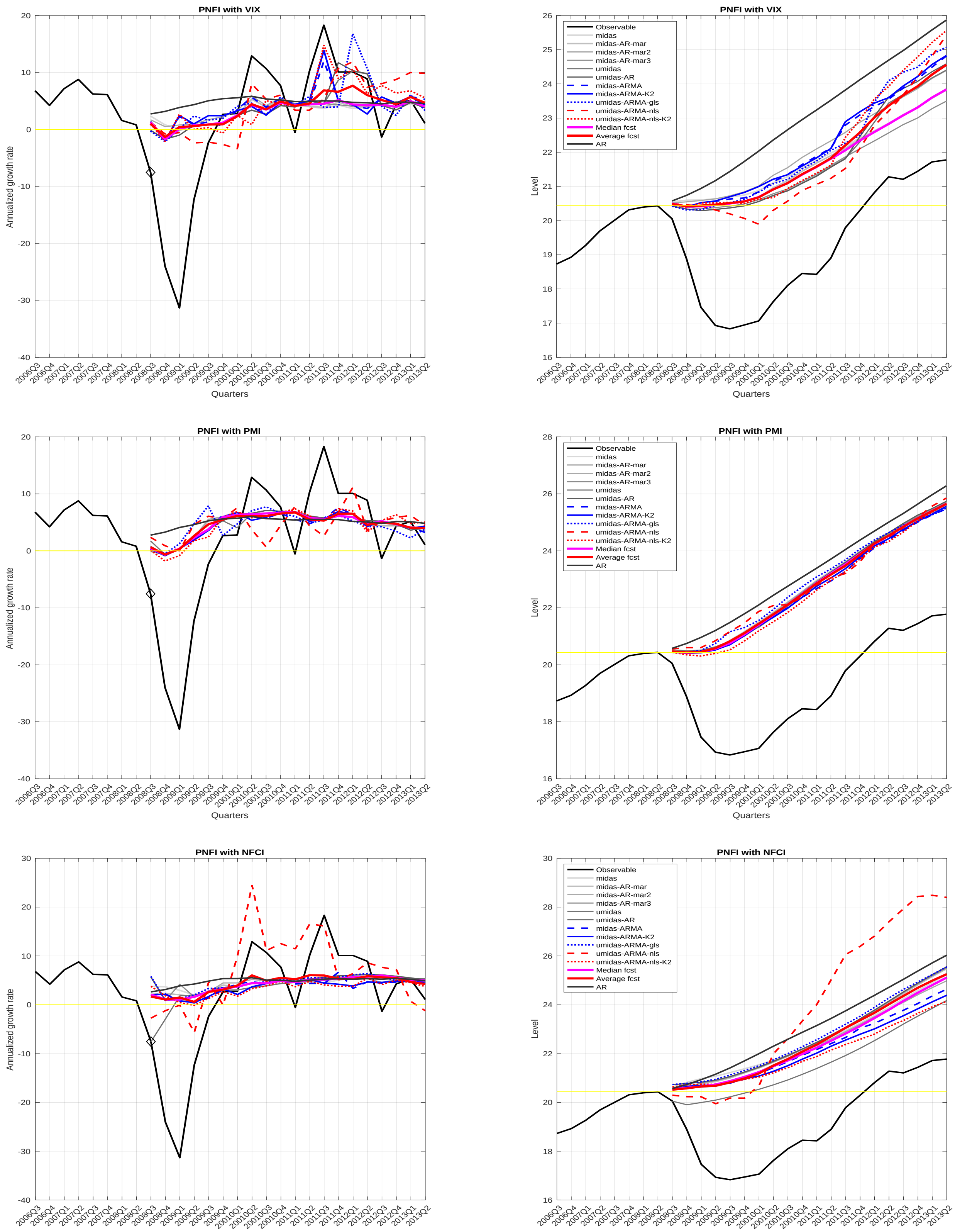


Figure 25: Adjusted forecasts of COVID recession and recovery

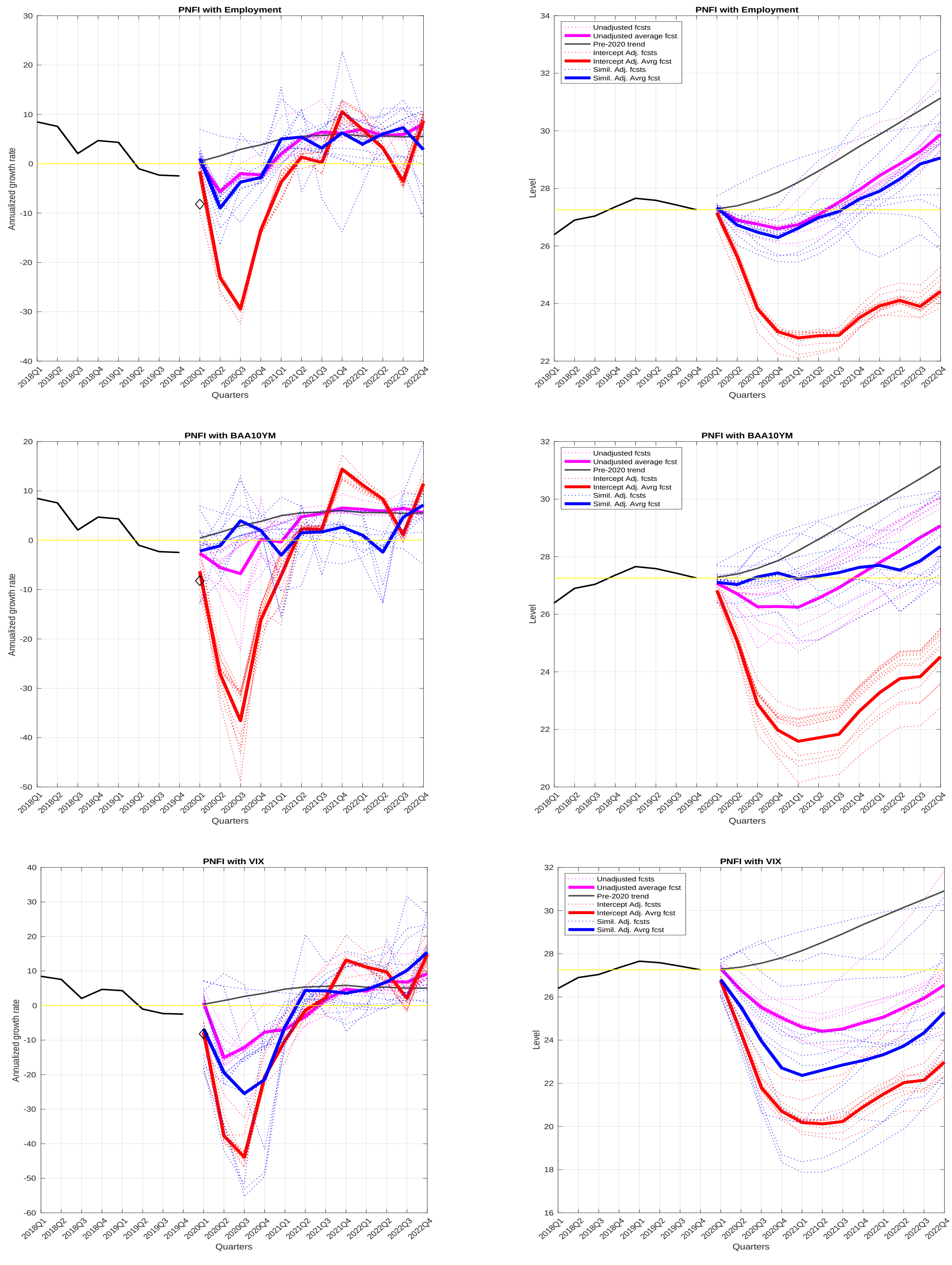


Figure 26: Adjusted forecasts of COVID recession and recovery, cont.

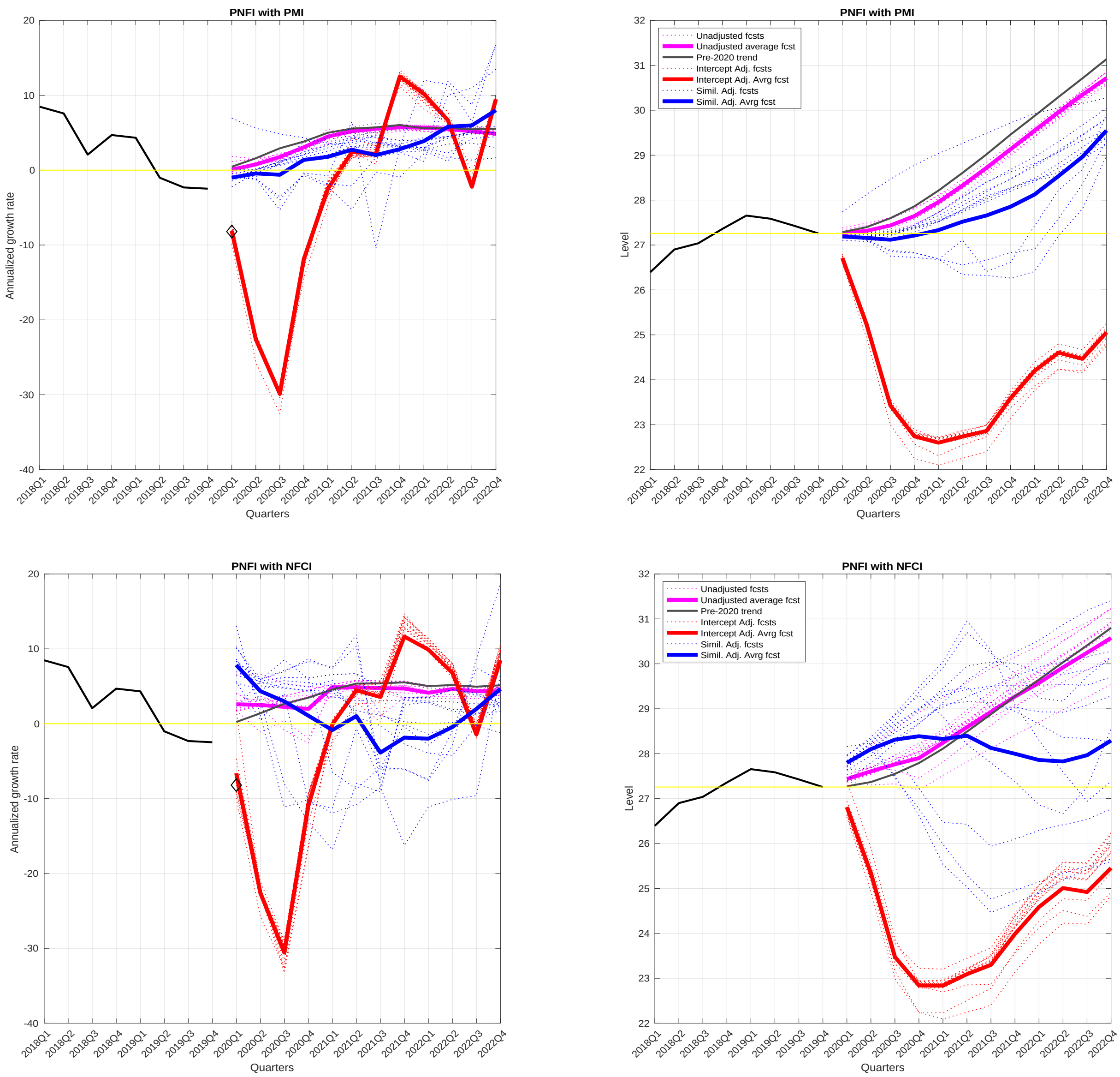


Table 6: Relative predictive accuracy: US investment with all indicators

	IP		EMP		BAA10Y	
Models	RMSE	MAE	RMSE	MAE	RMSE	MAE
AR	12.00	8.25	12.00	8.25	12.00	8.25
midas	0.59	0.67	0.73	0.71	0.87	0.92
midas-AR-mar	**0.54**	**0.57**	0.72	0.69	0.93	0.99
midas-AR-mar2	0.60	0.66	0.74	0.73	0.91	0.96
midas-AR-mar3	0.58	0.62	0.73	0.70	0.91	0.97
umidas	0.59	0.65	0.71	0.68	0.88	0.92
umidas-AR	0.59	0.65	0.72	0.69	0.88	0.96
midas-ARMA	0.57	0.60	0.73	0.74	0.88	0.92
midas-ARMA-K2	0.67	0.74	0.73	0.72	0.86	0.90
umidas-ARMA-gls	1.10	1.26	0.85	0.87	0.90	0.98
umidas-ARMA-nls	0.62	0.69	0.74	0.75	0.88	0.93
umidas-ARMA-nls-K2	0.69	0.78	0.73	0.70	0.81	0.85
Median fcst	0.59	0.65	0.72	0.69	0.87	0.94
Average fcst	0.61	0.65	0.73	0.70	0.88	0.94

	VIX		PMI		NFCI	
Models	RMSE	MAE	RMSE	MAE	RMSE	MAE
AR	11.97	8.30	12.00	8.25	11.95	8.28
midas	0.92	0.94	0.89	0.91	0.99	0.99
midas-AR-mar	0.88	0.90	0.89	0.91	0.95	0.94
midas-AR-mar2	0.91	0.90	0.89	0.91	0.92	0.92
midas-AR-mar3	0.88	0.90	0.89	0.89	0.96	0.94
umidas	0.86	0.81	0.89	0.89	0.89	0.86
umidas-AR	0.86	0.81	0.89	0.90	0.94	0.94
midas-ARMA	0.89	0.89	0.88	0.89	0.93	0.93
midas-ARMA-K2	0.89	0.88	0.89	0.92	0.94	0.94
umidas-ARMA-gls	0.89	0.89	0.93	0.93	0.94	0.94
umidas-ARMA-nls	0.88	0.91	0.97	1.05	0.85	0.85
umidas-ARMA-nls-K2	0.89	0.84	0.87	0.90	0.93	0.93
Median fcst	0.88	0.89	0.89	0.91	0.93	0.93
Average fcst	0.87	0.85	0.90	0.92	0.92	0.90

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