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Incorporating judgment in forecasting models in times of crisis

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Abstract

This paper introduces a simple and reproducible method to modify model forecasts using expert forecasts which is useful in crisis times. The idea is to add the expert forecast as an additional observation of the dependent variable, and to extend the model with an additional explanatory variable such as the square of a deterministic trend. Next, the new model forecast is combined with the expert forecast using equal weights. We show that it works well for gross domestic product growth forecasts for 2020 for 12 countries and that it improves upon an equal-weighted combination of the original model forecast and expert forecast.

KEYWORDS

economic growth, expert forecasts, forecast combination, judgment, model forecasts

1 | INTRODUCTION

Important macroeconomic variables, such as real gross domestic product (GDP) growth, inflation, and unemployment are driven by shocks, see for example Bloom et al. (2018). Sometimes these shocks are caused by macroeconomic policy, such as interest rate changes or other monetary policies, and the consequences of these policy changes must be estimated and predicted. Sometimes these shocks are, however, unexpected while they do affect the (short run) future path of macroeconomic variables. One can think of the container vessel Ever Given being stuck in the Suez channel. And, sometimes these shocks are not only unexpected but also exceptionally large and as such have a major, long-lasting, or sometimes even permanent effect on the future of an economy. Think of such shocks as 9/11, the collapse of the Lehmann brothers, or, more recently, the start of the Covid pandemic in March 2020.

In times of such major shocks, one can appreciate that accurate forecasts are of tantamount importance. Yet, at the same time, creating accurate forecasts at such times is difficult, See Clark et al. (2020), Galbraith and van Norden (2019), Eicher et al. (2019), and Rossi (2021) for a few examples. Econometric time series models, in whichever variant,[1] are usually not well equipped to predict turning points, although they can be successful right after the major shock, given that one has access to data with a high enough frequency.[2] In contrast to econometric time series models, professional forecasters who to some extent may rely on econometric time series models and to some extent on their own judgment, may provide more accurate forecasts, at least if they pick up the news quick enough, see for example, Isiklar et al. (2006) and An et al. (2018), Armstrong and Green (2018), among others.

It is now useful to combine forecasts from econometric time series models and professional forecasters, often with equal weights, see Bunn (1985) and Genre et al. (2013) among the many examples where equal-weight combinations are most accurate. The conclusion that a combination of forecasts turns out to be successful also appears from the recent M4 competition, see Makridakis et al. (2020). In particular, one may wish to combine at the onset of crisis times, see for example Jansen and de Winter (2018).

There are at least two reasons why this combination can be improved to yield more accurate forecasts. The first is that the econometric time series model continues from the past, and misses the turning point, thereby making it less useful in an equal-weight

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forecast combination. The second is that professional forecasters can overreact, and when they then also herd, their consensus forecast may overshoot reality, see for example, Lamont (2002).

In this short paper, we propose a new combined forecast, which is based on a modification of the econometric time series model forecast by incorporating the consensus forecast as a new observation. A subsequently updated model forecast, following on re-estimation of the model parameters, can then be combined with the consensus forecast, and as such smoothen the combined forecast. Our approach extends on the proposed method in Faust and Wright (2009) as we update the model parameters. One may also rely on the combination of the original model forecast with the expert forecast, but this puts the model forecast at a lag, as it could not have included the information that is known to the expert. The idea is developed further in Section 2. As such, this method is a simple yet reproducible approach to explicitly incorporate judgment into a combination of forecasts. A very sophisticated approach is proposed in Kruger et al. (2017), which aims to do the same thing, but it comes at the cost that many additional decisions on configurations must be made. Yet, our method is simple and easy to do, and as analysts have to be transparent as to how they modified the model, the method is fully reproducible.

In a sense, our method involves a judgmental adjustment of a model-based forecast. Franses (2014) reviews various studies which indicate that such judgmental adjustment can lead to much more accurate forecasts, see also Armstrong and Collopy (1998), Bunn (1992), Fildes et al. (2009), Goodwin, (2000, 2002), Mathews & Diamantopoulous, (1989, 1990), and many more.

An illustration in Section 3 to predicting real GDP growth for the United States in 2020, the first year of the pandemic, when model-based predictions are made at the end of 2019 shows the merits of the new combined forecast. Section 4 examines how these new combined forecasts perform for 11 other countries and shows that more accurate forecasts can indeed be obtained. Section 5 concludes with limitations of the method and an outlook.

2 | THE MAIN IDEA

Consider an analyst who wishes to make a forecast for year $T+1$ for a key macroeconomic variable like real GDP growth, inflation, or unemployment. The analyst has data available until and including year T for the relevant variable and potentially for other variables, that together provide the input for an econometric time series model. This econometric time series model, which for our method can take any shape, is then used to create the prediction. This one-step-ahead forecast from an econometric time series model for a variable y_t, where the sample is $t = 1,2,3, \ldots, T$, is denoted as

$$f^{M}_{T+1|T},$$

where $T+1|T$ means that a forecast is made for horizon $T+1$ from origin T, and "M" denotes model. In macroeconomic practice, the frequency of t usually refers to years, and hence $T+1$ concerns the next year. Sometimes intra-year model forecasts are delivered. For example, the Netherlands Bureau for Economic Policy Analysis (CPB) in the Netherlands gives two quotes in year T for year $T+1$, as well as two quotes in year $T+1$ for year $T+1$. Here, we consider one-step-ahead forecasts for notational convenience, but for multiple-steps-ahead forecasts, similar issues hold.

Although the analysts shall have confidence in the quality of their own econometric time series model, they are also aware of the fact that an equal-weight combination of forecasts can improve on the quality of individual forecasts. See Bates and Granger (1969), Clemen (1989), and Timmermann (2006) for key references, and Armstrong and Green (2018) for a more recent summary of evidence.

Typically, the parameters in a macroeconomic forecasting model are updated each year, although for large macroeconomic models this may happen only once every few years. So, for horizon $T+1$, the analyst uses data up to T, while when forecasting for horizon $T+2$, the estimation sample becomes $t = 1,2,3, \ldots, T+1$ in case of recursive estimates, or $t = 2,3, \ldots, T+1$ in case of rolling estimates.

When the year of interest, that is $T+1$, proceeds, the latest information on the state of the economy comes in. International and local developments may impact the course of variables such as GDP growth, inflation, and unemployment. Small or large shocks may enter the economy.

This latest information usually comes in at a higher frequency than only annually. Information can come in at a monthly level, such as new inflation rates and industrial production indicators, while other news might come in per day, such as data from stock markets, or noneconomic news about wars or presidential issues. This poses a problem to (the creator of) the econometric time series model, as it is not straightforward how to immediately incorporate such higher frequency updates into the econometric time series model, and how to re-estimate the model parameters. This is even more cumbersome if the news deals with something completely unexpected or noneconomic, such as a pandemic or a natural disaster. So, this is also the moment when the combination with expert forecasts becomes relevant.

The analysts might now resort to manual adjustment of their own econometric time series model forecast. This is a cumbersome task, as there are no exact and replicable guidelines on how to precisely do this. See Franses (2014) and many more. There are optimal properties, but there are no guidelines. There are numerous studies that show that expert adjustment can be useful, see Fildes et al. (2009) for an influential study, and Franses et al. (2011) who show that all forecasts made at the CPB have some judgmental twist to the econometric model forecasts. At the same time, if an economy is at the brink of a new or different regime, the econometric time series model forecast becomes less useful, and as such also less useful in combination with other forecasts.

The main idea of this paper is now to rely on an expert, or professional forecaster, who provides quotes at a higher frequency, for example, every month and to incorporate these quotes into the data set that is used to estimate the parameters in the econometric time series model. This data set then extends to $T+1$, and with this new additional observation, the analyst can modify or update the model, re-estimate the parameters, and then provide a new prediction for $T+1$. This prediction

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is then equal to the fit of the new model at that observation $T + 1$. This new model forecast can then be used as a standalone forecast, but again it may be preferable to incorporate it into a new combined forecast.

Let us denote the forecast from a professional forecaster, or expert, as $f^{E}_{T+1|T}$. In our empirical illustration below, we will use the consensus (average) forecasts from the Consensus Forecasters,[3] but one may of course also decide to pick (or follow) single individual forecaster or a set of forecasters. In Appendix A there is an example of GDP forecasts for the United States made by a range of forecasters, on March 9, 2020, for 2020 and 2021.

In practice, it may be sensible for the analyst to combine the analyst's model forecast $f^{M}_{T+1|T}$ with an expert forecast $f^{E}_{T+1|T}$, like

$$f^{C}_{T+1|T} = \alpha f^{M}_{T+1|T} + (1 - \alpha) f^{E}_{T+1|T}, \tag{1}$$

where often the choice is made for $\alpha = 0.5$, although a range of alternative weights is possible, see Wang et al. (2023) for a detailed review of alternative ways to combine forecasts. There are at least three potential problems with this last approach of creating $f^{C}_{T+1|T}$. The first is, that when there really are substantial events (shocks) such as the arrival of Covid that may have an enormous impact, even a long-lasting or permanent impact, that then the model forecast can become very inaccurate. This inaccuracy may harm the quality of the combined forecast in Equation (1). One may now decide to downsize the value of α in the combination, but any guidelines on how to choose this new weight α do not exist. A further complication is that the new value of α must be based on just a single observation.

A second issue is that unexpected large shocks may make professional forecasters to overreact (Andreassen, 1990), and when they additionally also herd, their joint forecasts can be very off track. Indeed, econometric models do not overreact, it is people who do. Appendix B provides an example of GDP forecasts for 2020 made in April 2020, which is the month after the world became aware that a pandemic had started. The realized real GDP growth in 2020 was −2.77, as we will see below. It is clear that the new forecasts are substantially lower than 1 month before. In case of overreaction, it may now be potentially useful to downplay the contribution of the expert forecast $f^{E}_{T+1|T}$ in the combined forecast Equation (1). Again, any guidelines on exactly how to do that do not exist.

A final, and fundamental, issue is that an expert sees a model forecast and can decide to (manually) change the weights in Equation (1), whereas the econometric time series model, or the analyst, so to say, has no chance to revise the model forecast. It is precisely this last issue that is addressed in this paper, by proposing a simple method to modify the model. And as such, there will be more balance of the model and the expert in a new combined forecast.

Consider adding to the series for a variable y_t, where the sample is $t = 1,2,3, \ldots, T$, a new observation at time $T + 1$, and assume this new observation is equal to $f^{E}_{T+1|T}$. Now there are $T + 1$ observations for the variable y_t, to which a new model can be fitted. This new model can include an additional variable like a trend $t = 1,2,3, \ldots, T + 1$, or $\log(t)$ or t^2, or a certain new explanatory variable x_t, at least a variable that allows for a downward bending of the curve (because it is crisis). This is of course open to judgment. It is judgment indeed, but as long as one tells which variable is used, it is fully reproducible. With the estimated parameters for this new model, one can create a fitted value of y_{T+1}, say, $\hat{y}_{T+1}$, and take this fitted value as the new and updated model forecast, like

$$f^{M^*}_{T+1|T} = \hat{y}_{T+1}. \tag{2}$$

In the last step, one can combine the two forecasts into

$$f^{C^*}_{T+1|T} = \alpha f^{M^*}_{T+1|T} + (1 - \alpha) f^{E}_{T+1|T}. \tag{3}$$

In a sense, the expert contribution is used twice. In the next section, we will illustrate how this works for a specific case, and after that we apply this idea to a range of forecasts.

3 | ILLUSTRATION FOR USA REAL GDP GROWTH 2020

Consider real GDP growth in the United States for the years 1961 to and including 2019, as in Figure 1, and presume that we are interested in predicting real GDP growth in 2020, which is the year that the COVID pandemic started.

It so turns out, based on an inspection of the (partial) autocorrelation function for the data and the properties of the estimated residuals, that a small but adequate model for this time series is a first-order autoregression [AR(1)], that is,

$$y_t = \mu + \rho y_{t-1} + \varepsilon_t, \tag{4}$$

where ε_t is a zero mean uncorrelated time series with constant variance σ^2_{ε}. Hence, we take this model for our illustration purposes. Using ordinary least squares (OLS) for 58 effective observations (1962–2019), the parameters μ and ρ are estimated as 2.080(0.393) and 0.317(0.103) with standard errors in parentheses. The one-step-ahead forecast for 2020, from 2019 onwards, from the model in

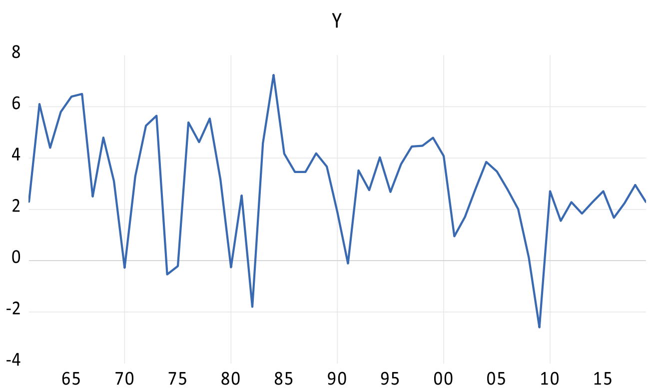

FIGURE 1 GDP growth (in percentages on the vertical axis) in the United States, 1961–2019 (years on the horizontal axis). *Source*: World Bank (consulted April 2023). GDP, gross domestic product.

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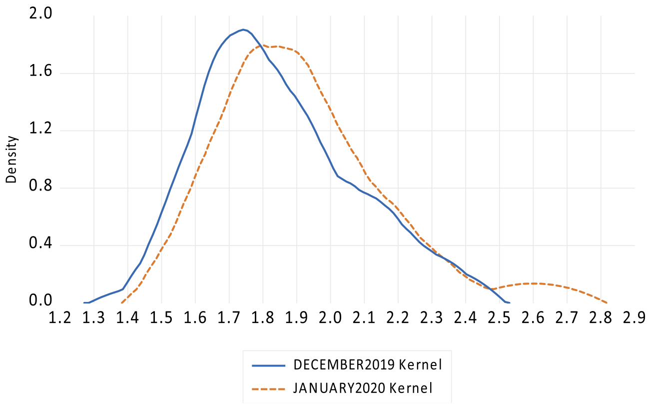

FIGURE 2 Kernels of forecasts from Consensus Forecasters for real GDP growth in the United States for 2020 where the forecasts are created in December 2019 and January 2020. GDP, gross domestic product.

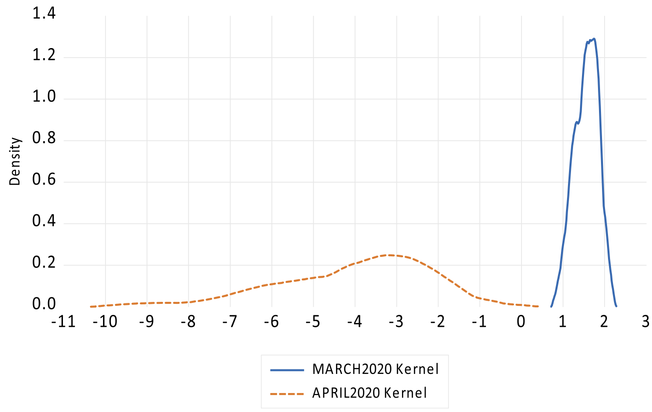

FIGURE 3 Kernels of forecasts from Consensus Forecasters for real GDP growth in the United States for 2020 where the forecasts are created in March 2020 and April 2020. GDP, gross domestic product.

Equation (4) is 2.81. Note that this simple AR(1) model is not per se the best model to use in a crisis, but in 2019 there was no sign of an upcoming crisis and hence, the AR(1) model could well be useful.

At the same time, there are forecasts from professional forecasters, here associated with Consensus Forecasters. Note that there are more collections of professional forecasters. Figure 2 displays the kernels of the forecasts for 2020, made in December 2019 and January 2020, respectively. We see that the professional forecasters on average quote around 2.0, which is slightly below the forecast from the above first-order autoregression

As time proceeds in 2020, the monthly forecasts from the professional forecasters become quite different, however. This is evident from the kernels of the forecasts as displayed in Figure 3. Not only does the average forecast change, from around 1.5 to −4.0, also the dispersion is quite different and is large for the quotes in April 2020. When we look at the kernels in Figure 4, for May 2020 and June 2020, we see that the averages move towards −6, while the dispersion seems to reduce.

Now we turn to creating a new model forecast, while incorporating the quotes of the professional forecasters. The average consensus forecast created April 6, 2020, is −4.00, the maximum quote is −1.35, and the minimum is −8.50. When we set the observation 2020 equal to −4.00, the average consensus forecast, we consider the following model for the effective sample 1962 to 2020, which now has 59 observations, that is,

$$y_t = \mu + \rho y_{t-1} + \gamma t^2 + \varepsilon_t,$$

where $t = 1,2,3,\ldots,\quad T+1$. Upon applying OLS, the parameters μ, ρ, and γ are estimated as 3.113(0.656), 0.220(0.138), and −0.000716(0.000266), respectively. The fitted value for 2020 is 1.12. Equal weights combining −4.00($f^{E}_{T+1|T}$) with 1.12 ($f^{M*}_{T+1|T}$) gives a new forecast $f^{C*}_{T+1|T}$ for 2020 equal to −1.44.

At present the actual reported observation for real GDP growth in 2020 is −2.77. The forecast error for the model M is −2.77 − 2.81 = −5.58, where 2.81 is the forecast from the AR(1)

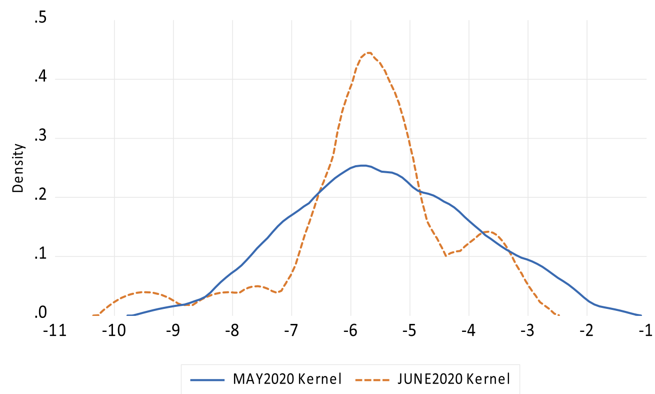

FIGURE 4 Kernels of forecasts from Consensus Forecasters for real GDP growth in the United States for 2020 where the forecasts are created in May 2020 and June 2020. GDP, gross domestic product.

model in Equation (4). The forecast error for the consensus forecasters is −2.77 − (−4.00) = 1.23. The forecast error for the equal weights combined forecast $f^{C}_{T+1|T}$ is $-2.77 - \frac{-4.00+2.81}{2} = -2.77 + 0.59 = -2.18$. And the forecast error for the new equal weights combined forecast $f^{C*}_{T+1|T}$ is −2.77 − (−1.44) = −1.33.

With this first illustration we see that forecast $f^{C*}_{T+1|T}$ is more accurate than $f^{C}_{T+1|T}$. Also, $f^{E}_{T+1|T}$ is much more accurate than $f^{M}_{T+1|T}$.[4]

When we move to the forecasts made in May 2020, results become even more striking. The average forecast of the Consensus forecasters for 2020 made in May 2020 is −5.429. The fitted value $\hat{y}_{T+1}$, based on the same model as before with the quadratic trend, is 0.98. The forecast $f^{C*}_{T+1|T}$ now is −2.22 and the associated forecast error is 0.55. The forecast error for $f^{E}_{T+1|T}$ is −2.66. Finally, the forecast error for the original combination $f^{C}_{T+1|T}$ is −1.46. Hence, the forecast $f^{C*}_{T+1|T}$ provides a substantial improvement over the other alternatives.

Finally, as the average Consensus Forecasters quote for 2020 made in June 2020 is −5.640, qualitatively equivalent results as for May 2020 will be obtained.

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4 | GDP GROWTH FORECASTS FOR 11 OTHER COUNTRIES

To examine if the idea to introduce judgment in the econometric time series model by extending the estimation sample has more general merit in practice, we now consider forecasts for real GDP growth in 2020 for 11 countries other than the United States. These countries are Germany, Japan, France, the United Kingdom, Italy, Canada, the Netherlands, Norway, Spain, Sweden, and Switzerland. Again, the professional forecasts are the consensus forecasts from Consensus Forecasters.

We consider six types of forecasts. The first is a model forecast $f^{M}_{T+1|T}$ based on a univariate time series model for the available data until 2019. This model is either an autoregression of order one or order two, depending on diagnostics for residual autocorrelation and the (partial) autocorrelations of the data. The second forecast is based on the average of 4 months of observations, created again by Consensus forecasts, where these 4 months are December 2019 to and including March 2020. The next forecasts are based on the average of 3 months of observations, again by Consensus forecasters, and these months are April 2020 to June 2020. Hence, these are the 3 months right after the world became aware of the COVID pandemic. The fourth set of forecasts are equal-weight forecasts of the model and the Consensus forecasters, $f^{C}_{T+1|T}$, where the Consensus forecasts are those created in April 2020 to June 2020. The fifth set of forecasts are based on the new model forecasts, $f^{M^*}_{T+1|T}$, where the observation in 2020 is set as the average of the April 2020 to June 2020 Consensus forecasts and where the new model includes t^2, additional to the autoregressive terms. Finally, the sixth set of forecasts, $f^{C^*}_{T+1|T}$, is an equal-weight combination of this new model forecast with the Consensus forecasts for April 2020 to June 2020. We compute for each of these forecasts the forecast error.

The results are displayed in Table 1. The average forecast error of the pure model-based forecasts is −7.53 and the median is −6.31, with exceptional errors for the United Kingdom (−13.23) and the smallest error for Norway (−2.48). As for the United States, and not unexpectedly, we see that the model-based forecasts by far could not foresee the consequences of the COVID outbreak. Equivalent results are obtained for the Consensus forecasts based on the 4 months of December 2019 to and including March 2020. The mean forecast error, over 11 countries, is −6.67 and the median forecast error is −5.21. These forecast errors are slightly smaller than those from the time series models, but also the professional forecasters did not foresee the substantial impact of the COVID outbreak.

The third column of Table 1 reports the forecast errors for the averaged Consensus forecasts, when made in April 2020 to June 2020. The average forecast error over 11 countries is 0.79 and the median is 0.53. Exceptionally accurate forecasts are delivered for Japan, France, Italy, and Canada, while for Norway, Germany, Sweden, and Switzerland, the professional forecasters seem to overreact. When we combine the model-based forecasts with the average Consensus forecasts, as reported in the fourth column, we get an average forecast error of −3.32 with a median of −2.56. Here we clearly see the consequence of combined inaccurate model-based forecasts with, on average, rather accurate expert forecasts. As expected, though, these new combinations are more accurate than the original model-based forecasts for all 11 countries.

TABLE 1 Forecast errors for six forecasts for GDP growth in 2020, for 11 countries.

	Method					
Country	A	B	C	D	E	F
Germany	−5.80	−4.47	2.23	−1.75	−4.03	−0.90
Japan	−5.30	−4.59	0.18	−2.56	−2.99	−1.41
France	−9.91	−8.84	−0.03	−4.97	−7.66	−3.85
United Kingdom	−13.23	−12.06	−3.61	−8.42	−11.61	−7.61
Italy	−10.35	−9.11	0.30	−5.02	−7.09	−3.39
Canada	−7.41	−6.74	0.53	−3.44	−5.01	−2.42
Netherlands	−6.31	−5.21	1.74	−2.28	−4.29	−1.27
Norway	−2.48	−2.58	5.58	1.55	−0.72	2.44
Spain	−13.55	−12.95	−3.12	−8.33	−11.80	−7.46
Sweden	−4.52	−3.23	2.37	−0.59	−3.32	0.01
Switzerland	−4.01	−3.56	2.56	−0.73	−3.14	−0.29
Mean	−7.53	−6.67	0.79	−3.32	−5.61	−2.38
Median	−6.31	−5.21	0.53	−2.56	−4.29	−1.41

Note: The six methods are A: Model forecast (based on data until 2019), B: December 2019-March 2020 (Consensus forecasters), C: April 2020 to June 2020 (Consensus Forecasters), D: April 2020 to June 2020 (Equal weights model forecast and consensus forecasters), E: April 2020 to June 2020 (New model forecasts), and F: April 2020 to June 2020 (Equal weights new model forecast and consensus forecasters).
Abbreviation: GDP, gross domestic product.

The fifth column in Table 1 provides the forecast errors based on an updated model. The average error across 11 countries is −5.61, and the median error is −4.29. Hence, the updated model forecasts improve on the original model-based forecasts. Finally, the sixth column reports on the forecast errors of the new combination, and then the average forecasts error across 11 countries is −2.38 and the median error is −1.41. Overall, this improves upon the earlier combination.

For four countries this last combination $f^{C^*}_{T+1|T}$ provides overall the most accurate forecast, while for six countries the expert (consensus) forecasts, $f^{E}_{T+1|T}$, based on the months April to June of 2020 are most accurate.

5 | CONCLUSION

This short paper introduced a simple and reproducible method to modify original model forecasts at the onset of crisis times while using expert forecasts. This method could prevent that inaccurate model forecasts are combined with (potentially) inaccurate expert forecasts due to overreaction. And, at the same time, it gives

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the new model forecast a fairer chance to successfully contribute to a combined forecast. An illustration for GDP forecasts for 2020 and for 12 countries showed the potential merit of this method.

Of course, this method also has its limitations. One such limitation is that one needs to modify the model, based on one single extra observation. This involves judgment on the new to include additional variable. If it is clearly told which variable, one can replicate the outcomes. The second is that the new method could work only in case of exceptional situations. Hence, only at the onset of a recession, or at the end of it when there is a steep recovery, this new method can be useful. Further empirical experience with a variety of cases of crisis shall tell how useful this new method is.

Yet, one may wonder whether the new method should only be used in crisis times. Perhaps it is useful in normal times too. This is an interesting avenue for further research, while using actual data and also simulation experiments.

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DATA AVAILABILITY STATEMENT

Data can be obtained from the author upon request.

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ENDNOTES

[1] Think of univariate time series models, exponential smoothing methods, vector autoregressions, Bayesian models, machine learning tools, panel data models, and many more.

[2] Think of nonlinear models like regime-switching models or neural networks, see De Gooijer (2017) for an excellent overview of nonlinear time series models.

[3] www.consensusforecasters.com

[4] We also considered the model estimates when OLS was applied for the data range 1990 to 2019, and when t^2 was replaced by log (t). For these three new configurations, the results are qualitatively similar.

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APPENDIX A

See Table A1

TABLE A1 Consensus forecasts for GDP growth in the United States for 2020 and 2021, created on March 9, 2020.

	Gross domestic product Real, % change	
Survey date: March 9, 2020	**2020**	**2021**
Consensus (mean)	1.560	2.030
High	2.000	2.800
Low	1.000	1.210
Standard deviation	0.270	0.303
Number of forecasts	25	25
First Trust Advisors	2.000	2.800
Citigroup	1.969	1.907
Nat ASSN of Home Builders	1.900	1.800
Macroeconomic Advisers	1.833	1.776
BBVA	1.826	1.972
FedEx Corporation	1.705	1.906
Inforum—Univ of Maryland	1.702	2.198
Dynamic Econ Strategy	1.700	2.200
Econ intelligence unit	1.700	1.900
Fannie Mae	1.700	2.300
Royal Bank of Canada	1.700	1.900
PNC financial services	1.668	2.005
Eaton Corporation	1.643	2.235
Bank of America—Merrill	1.636	1.764
Ford Motor Company	1.519	2.030
JP Morgan	1.450	1.843
Georgia State University	1.400	1.210
Wells Fargo	1.400	2.300
Moody's Analytics	1.347	2.413
Oxford Economics	1.343	1.987
CIBC World Markets	1.330	1.933
Goldman Sachs	1.218	2.327
Robert Fry Economics	1.200	2.300
Swiss Re	1.100	1.750
BMO Capital Markets	1.000	2.000

Abbreviation: GDP, gross domestic product.

APPENDIX B

See Table B1

TABLE B1 Consensus forecasts for GDP growth in the United States for 2020 and 2021, created on March 9, 2020.

	Gross domestic product Real, % change	
Survey Date: April 6, 2020	**2020**	**2021**
Consensus (mean)	−4.003	3.870
High	−1.349	7.669
Low	−8.495	0.917
Standard deviation	1.692	1.813
Number of forecasts	24	24
Royal Bank of Canada	−1.349	2.667
Eaton Corporation	−2.081	3.333
Moody's Analytics	−2.173	2.679
PNC Financial Services	−2.691	3.834
Univ of Michigan—RSQE	−2.804	2.873
Dynamic Econ Strategy	−2.900	1.800
Econ Intelligence Unit	−2.900	1.600
First Trust Advisors	−2.900	3.200
Wells Fargo	−3.000	1,700
Swiss Re	−3.018	2.864
CIBC World Markets	−3.270	4.815
BBVA	−3.421	3,391
Fannie Mae	−3.600	5.000
Inforum—Univ of Maryland	−3.700	3.600
BMO Capital Markets	−4.000	5.500
Oxford Economics	−4.095	7.669
Nat Assn of Home Builders	−4.642	4.577
JP Morgan	−5.341	4.487
IHS Markit	−5.378	6.326
Ford Motor Company	−5.664	6.084
Bank of America—Merrill	−5.954	1.700
Goldman Sachs	−6.216	5.510
Georgia State University	−6.469	0.917
Robert Fry Economics	−8.495	6.764

Abbreviation: GDP, gross domestic product.

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