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Forecasting in the Absence of Precedent

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Forecasting in the Absence of Precedent

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Abstract

We survey approaches to macroeconomic forecasting during the COVID-19 pandemic. Due to the unprecedented nature of the episode, there was greater dependence on information outside the econometric model, captured through either adjustments to the model or additional data. The transparency and flexibility of assumptions were especially important for interpreting real-time forecasts and updating forecasts as new data were observed. With data available at the time of writing, we show how various assumptions were violated and how these systematically biased forecasts.

Key Words: Macroeconomic Forecasting, COVID-19

1 Introduction

The COVID-19 pandemic and the ensuing recession has posed challenges for forecasters. The size of the fluctuations has been unprecedented, with GDP declining by 9% in 2020Q2, compared to a maximum quarterly decline of 2% in the Great Recession. In addition, the nature of the shock is different than past recessions. Economic activity declined due to social distancing measures rather than, for instance, financial shocks.

In the presence of large and atypical fluctuations in the economy, the challenge for the econometrician is to construct informative forecasts in the absence of data on the new circumstances of the pandemic. There is thus a particularly important role for sources of information outside what one might typically use. The first source is subjective judgement or prior knowledge, typically from economic theory. Alternatively, one can consider external sources of data. For instance, epidemiological data was of special interest during the pandemic. However, the value of the additional data depends on knowledge of its joint distribution with the variables of interest, which was not always easy to determine initially.

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[†]The views expressed herein are those of the author and do not necessarily represent the views of the Federal Reserve Bank of Richmond or the Federal Reserve System.

This essay discusses the literature dealing with these challenges during the COVID-19 pandemic. We highlight assumptions underlying each approach and argue that knowledge of the pandemic could have been used to interpret and improve these forecasts. We then discuss what the data through December 2020 tell us about the validity of various assumptions.

2 The Forecasting Problem

2.1 Adapting Economic Models to Unprecedented Times

In adapting our models to allow for the changes in the economy, one needs to acknowledge the difference in circumstances without going to the extreme of completely ignoring what has been learnt from past experience. In addition, the particular circumstances can make new data either unusually informative or misleading, depending on whether one is able to appropriately discern how the different variables evolve jointly.

Economic Knowledge. The econometrician needs to translate her interpretation of the data's large fluctuations into model assumptions. This requires subjective judgement informed by economic theory or knowledge outside the model. Is the variation in data explained by large shocks, new shocks, or a different propagation of shocks? These questions have also been asked in attempts to account for previous changes in the behavior of macroeconomic data (e.g., [Cogley and Sargent \(2005\)](#); [Sims and Zha \(2006\)](#); [Stock and Watson \(2012\)](#)).

Assumptions in the model should be easily communicated. Transparent assumptions allow the audience to understand forecasts within the context of the model. For example, if the model assumes an unchanged persistence but it is understood that the current recession is likely to be less persistent than past experience, then one can take the model forecast as providing an overestimate of the depth of the recession in the medium run.

In addition, where possible, assumptions should be imposed probabilistically. For example, even if one believed that past experience was a good benchmark for how the COVID-19 recession may play out, one can impose that the model parameters are “probably close”—rather than identical—to what they were before the pandemic. This allows us to update our parameter estimates as we observe new data. At the time of writing, we are still in the middle of the pandemic, but have over a year of data on the evolution of both economic and epidemiological variables. Even with decades of data, artificially tight prior assumptions can bias model predictions in ways that are often hard to detect (e.g., [Canova and Sala \(2009\)](#); [Giannone et al. \(2015\)](#); [Ho \(2020\)](#)), a problem that is exacerbated when data are relatively scarce. Moreover, these assumptions can give a false sense of precision in forecasts.

The above features are especially important in the context of the COVID-19 pandemic. Given disagreement among economists and policymakers, clear communication is crucial for making quantitative model forecasts useful beyond the narrow audience that fully agrees with the model assumptions. Since individual econometricians were themselves probably less certain about the new

structure of the economy, the probabilistic presentation of assumptions results in forecast error bands that more accurately reflect the econometrician’s own degree of confidence.

Additional Data. The COVID-19 pandemic was a striking example of when new data sources became especially useful. The public health dimension of the economic fallout made data on COVID-19 cases, hospitalizations, and deaths important. In addition, the fast-moving nature of the crisis brought a new demand for high frequency data to inform economists and policymakers of the state of the economy before the usual quarterly or even monthly data were published. Beyond raw data, forecasts of the pandemic were and continue to be of interest (e.g., [Ho et al. \(2020\)](#); [Atkeson et al. \(2021\)](#); [Li and Linton \(2021\)](#); [Liu et al. \(2021\)](#)).

The question of how to integrate these data into model forecasts of the economy returns us to the question of model specification. Assumptions need to be made about the relationship between the additional data series and the variables one was looking at previously. If these assumptions are misguided, incorporating the additional data can lead one to misleading conclusions about the current and future state of the economy.

2.2 Formal Framework

Model. To formally organize our discussion, we consider the vector autoregression (VAR):

$$X_t = BX_{t-1} + C\varepsilon_t, \tag{1}$$

where X_t is a vector of current and lagged macroeconomic variables, and $\varepsilon_t \sim \mathcal{N}(0, I)$ is a vector of orthogonal shocks normalized to each have variance one. The parameter C determines how a shock affects the economy on impact, and the parameter B captures how the shock then propagates through the economy.

Many forecasting models can be cast as special cases or extensions of this. For example, dynamic stochastic general equilibrium (DSGE) models and factor models take the form (1) with restrictions on B and C that arise from either economic or statistical restrictions derived from the respective models. The time-varying parameter (TVP) VAR (e.g., [Primiceri \(2005\)](#); [Lubik and Matthes \(2015\)](#)) takes the form (1) but allows B and C to vary over time. More involved methods, especially from the field of machine learning, have been used for macroeconomic forecasting before and during the COVID-19 recession (e.g., [Coulombe et al. \(2021\)](#); [Huber et al. \(2020\)](#)). While we do not provide a detailed description of these methods here, we note that these methods introduce a high degree of flexibility for the variables X_t to evolve differently during contrasting episodes, which can be thought of as less parametric approaches to the ideas in Section 3.1.¹

¹While [Coulombe et al. \(2021\)](#) find that machine learning methods improved forecasting performance over certain benchmark linear models similar to (1) during the pandemic, it is not clear how these methods compare to parametric extensions to (1), such as those discussed in Section 3.1. In addition, machine learning methods and nonlinear models more generally have not been found to have systematic benefits over linear models before the pandemic (see [Ferrara et al. \(2015\)](#) and [Coulombe et al. \(2021\)](#) for details).

Forecasting. Suppose all the parameters are known. Then the optimal forecast h periods ahead is $B^h X_t$. One can also condition on a future path for a subset of variables in X_t to derive forecasts for the rest of X_t .

Uncertainty in the forecast arises from two sources. First, there is uncertainty about future ε_t . The coefficient C directly scales the level of this uncertainty by changing the variance of the errors $C\varepsilon_t$. The coefficient B also impacts uncertainty by influencing the propagation of the shocks ε_t . For example, if B implies a very persistent system, then shocks today can have a lasting impact on macroeconomic outcomes far in the future. As a result, the value of X_t not only depends on the contemporaneous shock, but is also heavily driven by past shocks, thus increasing the variance. Second, there is uncertainty about the parameter values for B and C . Even if one knew all future realizations of ε_t , the way these impact X_t depends on the parameter values.

Unusual Times. The challenge in uncertain times such as the COVID-19 pandemic, is that the recent parameters are probably not the ones governing the evolution of the data X_t in the near future. The large share of temporary layoffs made the initial shock to unemployment less persistent than in the past (i.e., B was closer to 0). The speed with which social distancing measures were adopted (both by policy and individual decisions) resulted in larger and more sudden changes in the economy (i.e., a larger scale of C). The fact that the public health outcomes started playing a role in business cycle fluctuations that they never had in recent history suggests that there may be new data series or shocks to consider (i.e., additional relevant series in X_t or new shocks in ε_t).

Typically, one might rely on the data to update our estimates rather than impose assumptions on how the parameters have changed, potentially through a TVP-VAR that allows parameters to adjust to the new circumstances. However, the fast-moving nature of the pandemic required forecasts before sufficient data had been observed to reliably update the parameters. The absence of data and knowledge that circumstances had changed meant that econometricians have had to choose how to impose their knowledge of current events on the model forecasts. Moreover, the uniqueness of the crisis increases uncertainty about what is known before seeing data. For instance, while there is a rich literature of DSGE models studying typical recessions, quantitative models of the public health dimension of the COVID-19 crisis have not been widely studied. The literature has struggled real-time with this—not only is there qualitative disagreement about economic events, but the high dimensionality of many forecasting models presents challenges to expressing qualitative views and knowledge quantitatively.²

3 Forecasting Approaches During the COVID-19 Pandemic

We now discuss four attempts to adapt forecasting methods to the COVID-19 pandemic.

²For instance, in the model (1), if X_t contained 12 lags of 6 variables, which is typical with monthly data, B would have 432 elements to be estimated.

3.1 Adapting the Model

The first two approaches focus on extensions to (1). We discuss how the results may have been influenced by particular assumptions that each paper makes about how the COVID-19 economy differs from the pre-pandemic economy.

3.1.1 Increasing Volatility

Lenza and Primiceri (2020) interpret the volatility in the economy during the pandemic as arising from a sequence of large shocks. In particular, they replace (1) with

$$X_t = BX_{t-1} + s_t C \varepsilon_t, \quad (2)$$

where the additional variable s_t determines how the variance of the shock varies over time. They assume $s_t = 1$ before the pandemic, estimate s_t for March, April, and May 2020, and assume a gradual (autoregressive) decay back to one subsequently. The idea of incorporating time-varying volatility in models is not new (e.g., Engle (1982); Jacquier et al. (2004); Stock and Watson (2016)). In the forecasting context, Clark (2011) shows that including time-varying volatility improves macroeconomic forecasting performance.

The change in variance captured in (2) is important for both estimation and forecasting. For estimation, acknowledging that recent data is subject to a large amount of noise ensures that the estimates for B and C are not overly impacted by the small number of outliers. Indeed, Lenza and Primiceri (2020) find that when they estimate (1) instead of (2) using data that includes the COVID-19 periods, the model produces unreasonable forecasts with explosive responses to shocks that can predict that the recession continually deepen without any end. Huber et al. (2020) provide an alternative approach to dealing with outliers using a nonparametric model. Their approach recognizes the increased uncertainty when the data look different than in the past, as was the case in 2020Q2 and 2020Q3. While Lenza and Primiceri (2020) attribute the difference to a large shocks, Huber et al. (2020) allow for a change in parameters.

For forecasting, since a large part of forecast uncertainty arises from the possibility of future disturbances, acknowledging the increased variance of shocks captures the increased uncertainty in forecasts. Carriero et al. (2021a) show that assumptions about the time-varying volatility s_t matter for forecasts. They distinguish between allowing s_t to fluctuate gradually (as a random walk both before and after the COVID-19 pandemic) and allowing for occasional one-off jumps in s_t . Because the March and April 2020 data were such huge outliers, allowing for occasional one-off jumps in the shock variances tightens forecast error bands, arguably making them more reasonable by allowing volatility to quickly return to closer to historical levels after the initial sharp adjustments to the pandemic. In related work, Carriero et al. (2021b) estimate a time-varying volatility VAR using data through June 2020 and find a substantial role for such one-off increases in volatility in a number of variables, including employment and industrial production.

There are two attractive features of the Lenza and Primiceri (2020) approach. First, the as-

assumptions are transparent to communicate. Even if one does not believe the exact model, the forecasts can be informative if one has a clear idea of the direction in which they are biased. Second, estimation is a straightforward application of generalized least squares.

There are two implicit assumptions that are potentially problematic:

1. Since B remains unchanged, the effect of a one time shock ε_t propagates through the economy the same way before and during the pandemic.
2. The variance of all shocks increases proportionally.

In other words, (2) treats the pandemic as merely a period with unusually high volatility even though there was an understanding early on in the pandemic that the COVID-19 recession would differ from previous recessions in terms of job losses, revenue losses, and consumer behavior. As a result, both the propagation of and the relative variance of shocks likely differed from the pre-pandemic data. These assumptions are dropped, for instance, in the TVP-VAR of [Primiceri \(2005\)](#) or [Lubik and Matthes \(2015\)](#).

[Lenza and Primiceri \(2020\)](#) present forecasts conditional on actual unemployment data through September 2020 and Blue Chip consensus forecasts for unemployment in subsequent months. They compare the forecasts from (2) to an estimation without accounting for the change in variance (using only pre-pandemic data for the estimation of the parameters). The conditional forecasts from June 2020, shown in [Figure 1](#), show that the inclusion of the time-varying variance substantially widens the forecast error bands, as the model predicts a future sequence of large shocks (i.e., large future s_t). In contrast, when a fixed variance is assumed, the forecast error bands are much narrower, with realized data falling outside or on the edge of the 95% credible region. [Figure 2](#) shows that the time-varying variance no longer has a significant effect on the size of the error bands when the forecast is made using data through September 2020. By this time, the estimated variance is closer to normal and parameter uncertainty is the main source of forecast uncertainty.

While the approach of [Lenza and Primiceri \(2020\)](#) helps account for uncertainty, it leaves the point forecasts relatively unchanged, reflecting a relatively unchanged coefficient B . Even though data from the COVID-19 period can potentially alter the estimate of B , the estimation places very low weight on these data due to their large variance, captured by s_t . For the conditional forecasts in [Figures 1](#) and [2](#), this turns out to be a reasonable assumption, as the distribution of employment, consumption, and prices conditional on unemployment did not change too much.³ We will show later that this was not true for other variables. In addition, the assumption of a constant B would have likely resulted in misleading unconditional forecasts. The highly persistent response of the economy to an unemployment shock, shown in [Figure 3](#), suggests that the model would not have predicted the relatively rapid decline in unemployment shortly after the start of the pandemic. The response is consistent with the historical behavior of employment but not necessarily the specific circumstances of the COVID-19 recession.

³The Blue Chip forecasts overpredicted unemployment, lowering forecasts for employment and consumption.

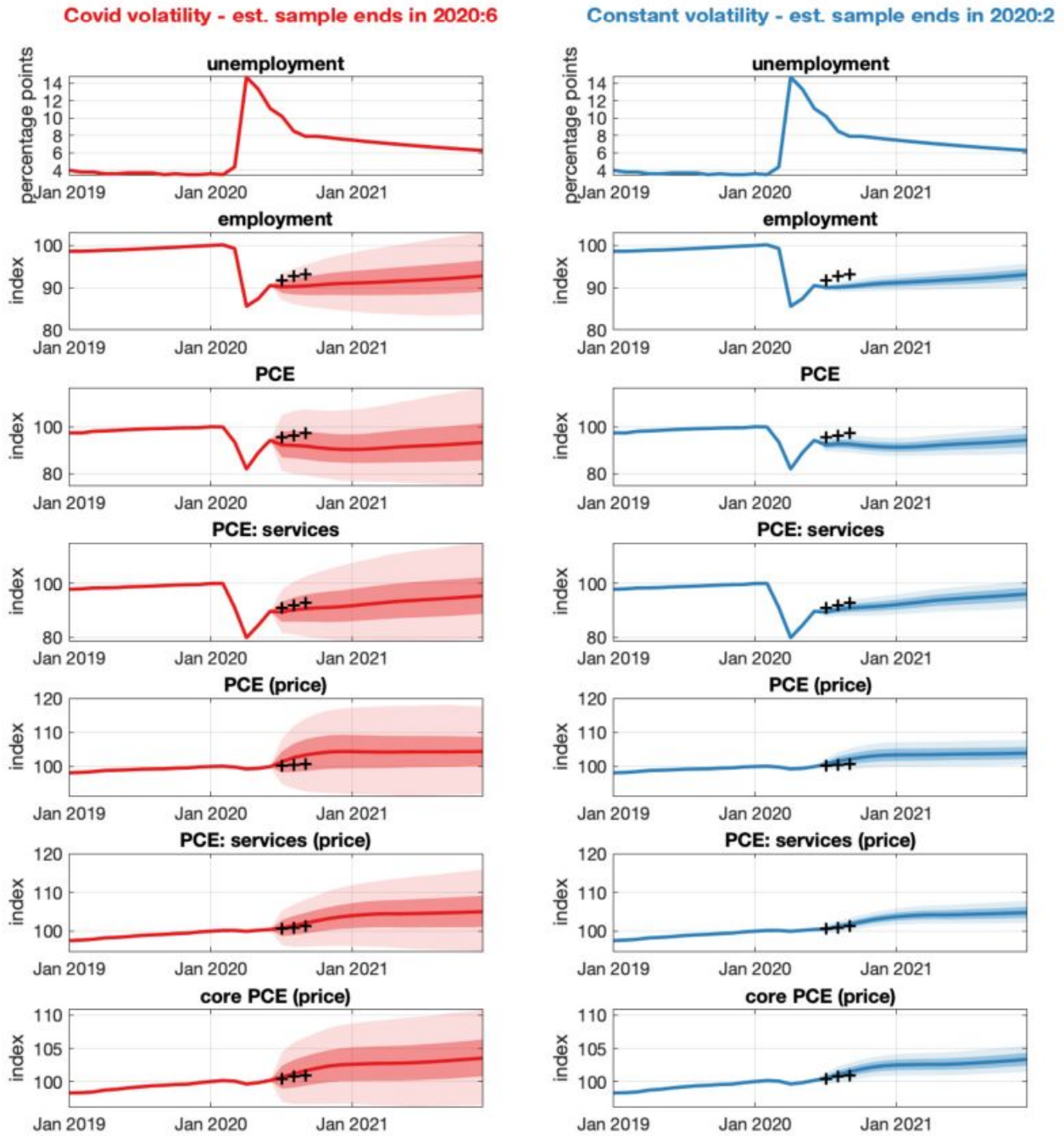


Figure 1: Figure 3 from [Lenza and Primiceri \(2020\)](#). Forecasts as of June 2020 conditional on path for unemployment (actual realizations until September 2020, Blue Chip consensus forecasts subsequently), 68% and 95% bands. Crosses are data realizations. **Left panel:** Estimation with change in volatility using data through June 2020; **Right panel:** Estimation with constant volatility using data through February 2020.

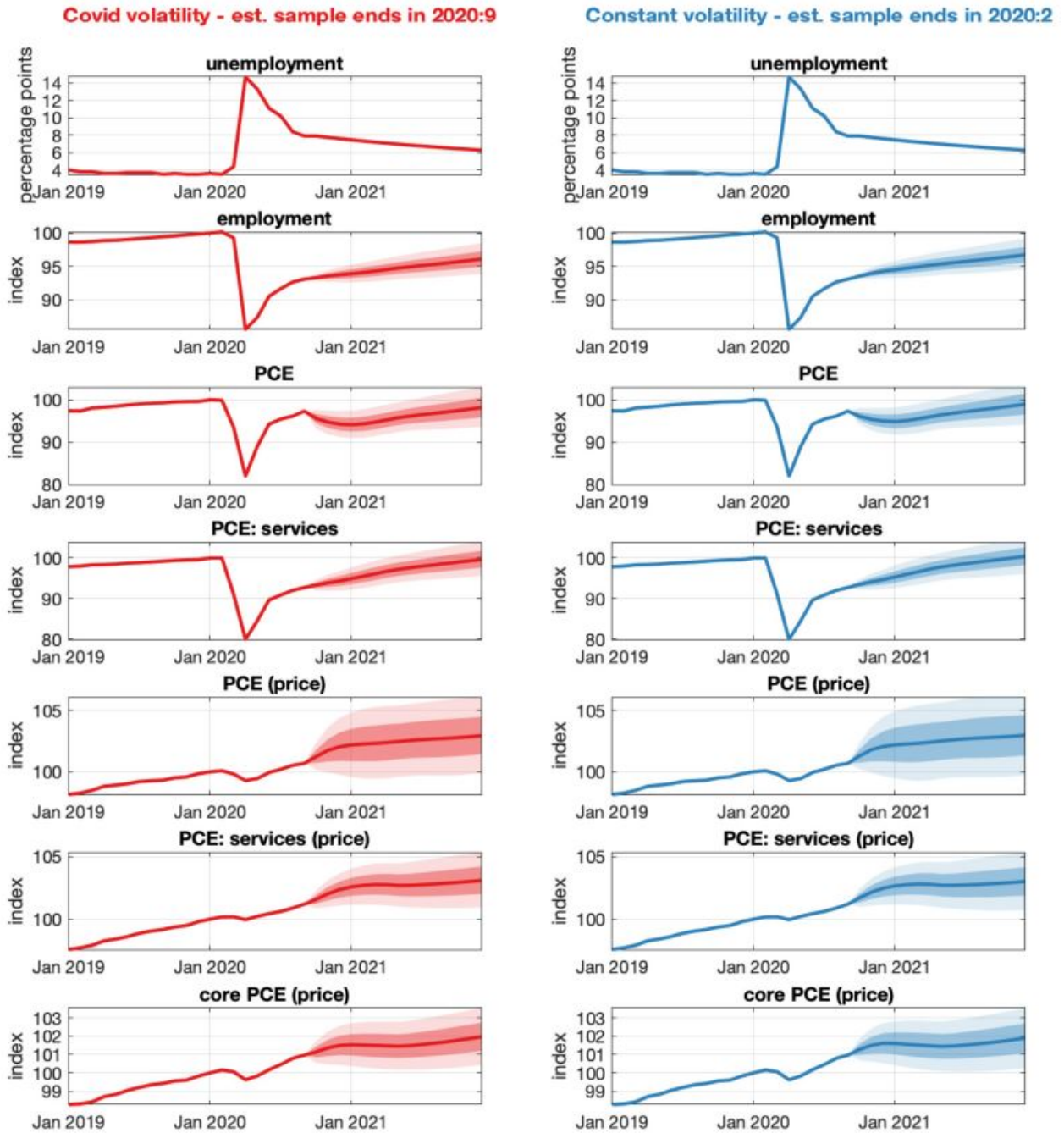


Figure 2: Figure 4 from [Lenza and Primiceri \(2020\)](#). Forecasts as of September 2020 conditional on path for unemployment (actual realizations until September 2020, Blue Chip consensus forecasts subsequently), 68% and 95% bands. Crosses are data realizations. **Left panel:** Estimation with change in volatility using data through September 2020; **Right panel:** Estimation with constant volatility using data through February 2020.

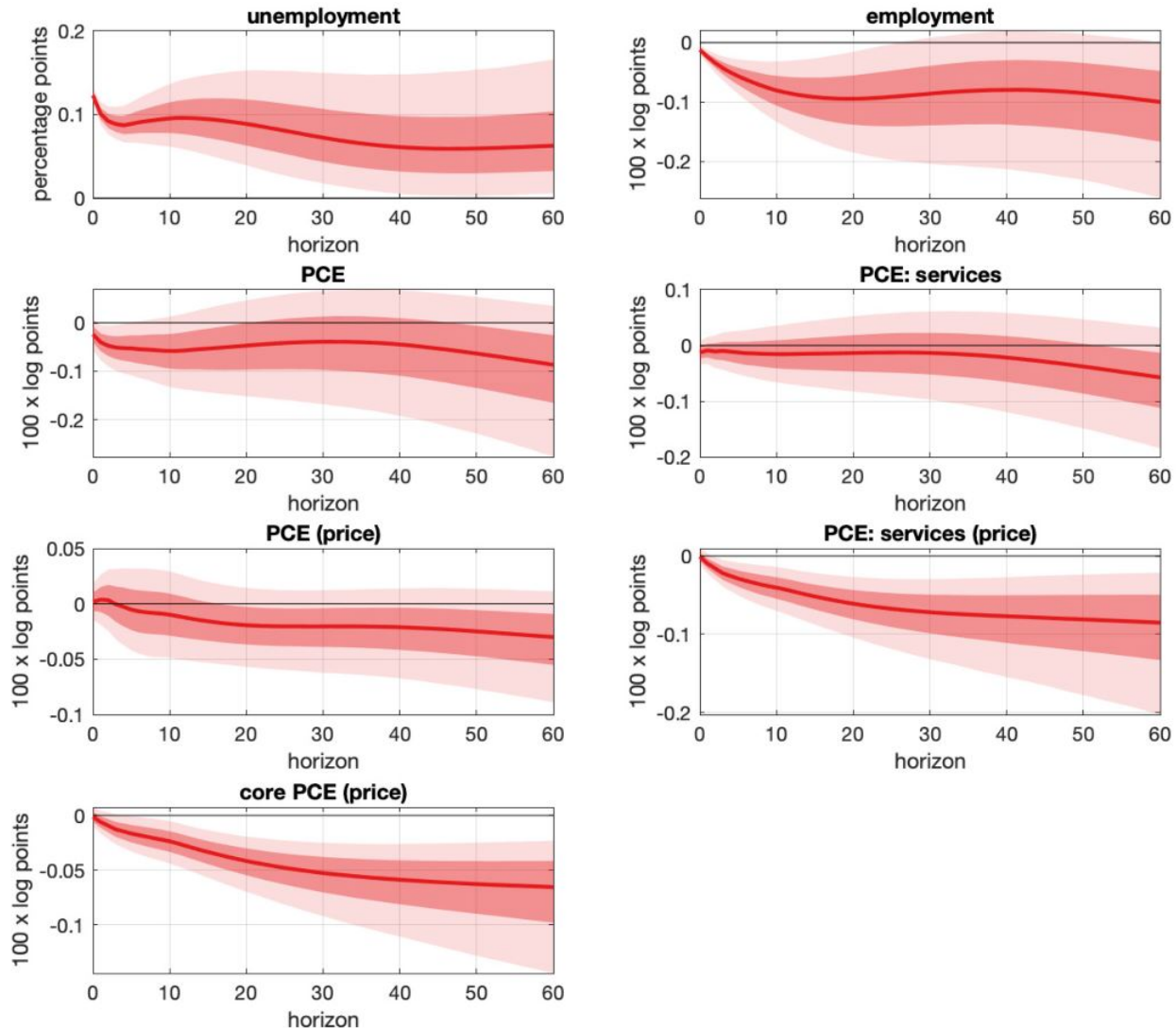


Figure 3: Figure 2 from [Lenza and Primiceri \(2020\)](#). Impulse response to a one standard deviation unemployment shock, 68% and 95% bands.

3.1.2 Introducing a New Shock

[Primiceri and Tambalotti \(2020\)](#) provide a framework that acknowledges that the COVID-19 shock is different than previous shocks, weakening the assumptions in [Lenza and Primiceri \(2020\)](#). We present a simplified version of their approach using the VAR model (1). Noting that (1) can be rewritten as $X_t = \sum_{s=0}^{\infty} B^s C \varepsilon_{t-s}$, with the data being explained by an infinite history of shocks, [Primiceri and Tambalotti \(2020\)](#) consider a version of the model:

$$X_t = \sum_{s=0}^{\infty} B^s C \varepsilon_{t-s} + \sum_{s=0}^{\infty} G^s H \circ v_{t-s}, \quad (3)$$

where v_t is the COVID-19 shock that takes the value zero before March 2020 and \circ denotes element-

wise multiplication.⁴

At its core, the above procedure is forecasting conditional on an unobserved variable v_t . The path of shocks is hypothetical but can in principle be derived from external data such as mobility measures or case numbers, as will be illustrated in Section 4. How successful and reasonable the forecasts are depend on the assumptions made about the path of the COVID-19 shock and its propagation through the economy. [Primiceri and Tambalotti \(2020\)](#) make three assumptions:

1. The variable v_t accounts for all unexpected variation of X_t in March and April 2020.
2. $G = B$, i.e., the way the shock propagates through the economy remains unchanged, similar to the assumption in [Lenza and Primiceri \(2020\)](#) that B remains unchanged.
3. The variable v_t is generated by a sequence of typical business cycle shocks, as defined based on a fully-specified DSGE model from [Justiniano et al. \(2010\)](#).

Assumption 1 is a reasonable approximation *ex ante* because COVID-19 has overshadowed all other typical variation in the economy. It is the typical assumption made in event studies.

Assumptions 2 and 3 are more controversial. Both assumptions treat the COVID-19 shock as typical even though the nature of the COVID-19 shock to the economy is vastly different from any recent experience. Moreover, the rigidity of the assumptions imply that incoming data have limited capacity to revise model estimates. Nevertheless, completely discarding past experience would result in overly uninformative forecasts. Even though the shock is unusual, the structure of the economy does not completely change overnight.

Forecasters should acknowledge the unprecedented situation while allowing the model to be informed by data. For the propagation of shocks, we consider the pre-pandemic value of B is a good benchmark but expect the economy to recover more rapidly than in previous recessions. This should be imposed probabilistically, replacing Assumption 2, so that we do not force our beliefs on the data but instead allow the forecasts to combine our beliefs with the available data. For the evolution of the shock, epidemiological model forecasts can replace Assumption 3 by providing informed predictions about the future path of the pandemic and uncertainty about that path.⁵

Through the lens of a TVP-VAR, the new shock in [Primiceri and Tambalotti \(2020\)](#) can be captured through a change in parameters. Starting with an initial belief about the parameter values that is centered at the pre-pandemic estimates, the TVP-VAR allows the data to inform the estimates of a potentially new set of parameters. The model has the flexibility to allow for changes in comovements, persistence, and variances.

Figure 4 shows that [Primiceri and Tambalotti \(2020\)](#) forecast a more persistent decline in economic activity than occurred. Their forecast conditions on v_t being close to zero from around January 2021, which has turned out to be an overly optimistic prediction. Nevertheless, even the

⁴More precisely, [Primiceri and Tambalotti \(2020\)](#) take $v_t = \sum_{s=0}^{\infty} r_s u_{t-s}$, where u_t is a scalar that takes value one in March 2020 and zero for all other months.

⁵For example, [Meza \(2020\)](#) implements the [Primiceri and Tambalotti \(2020\)](#) methodology for Mexican data, conditioning forecasts on the path of the pandemic predicted by a simple epidemiological model.

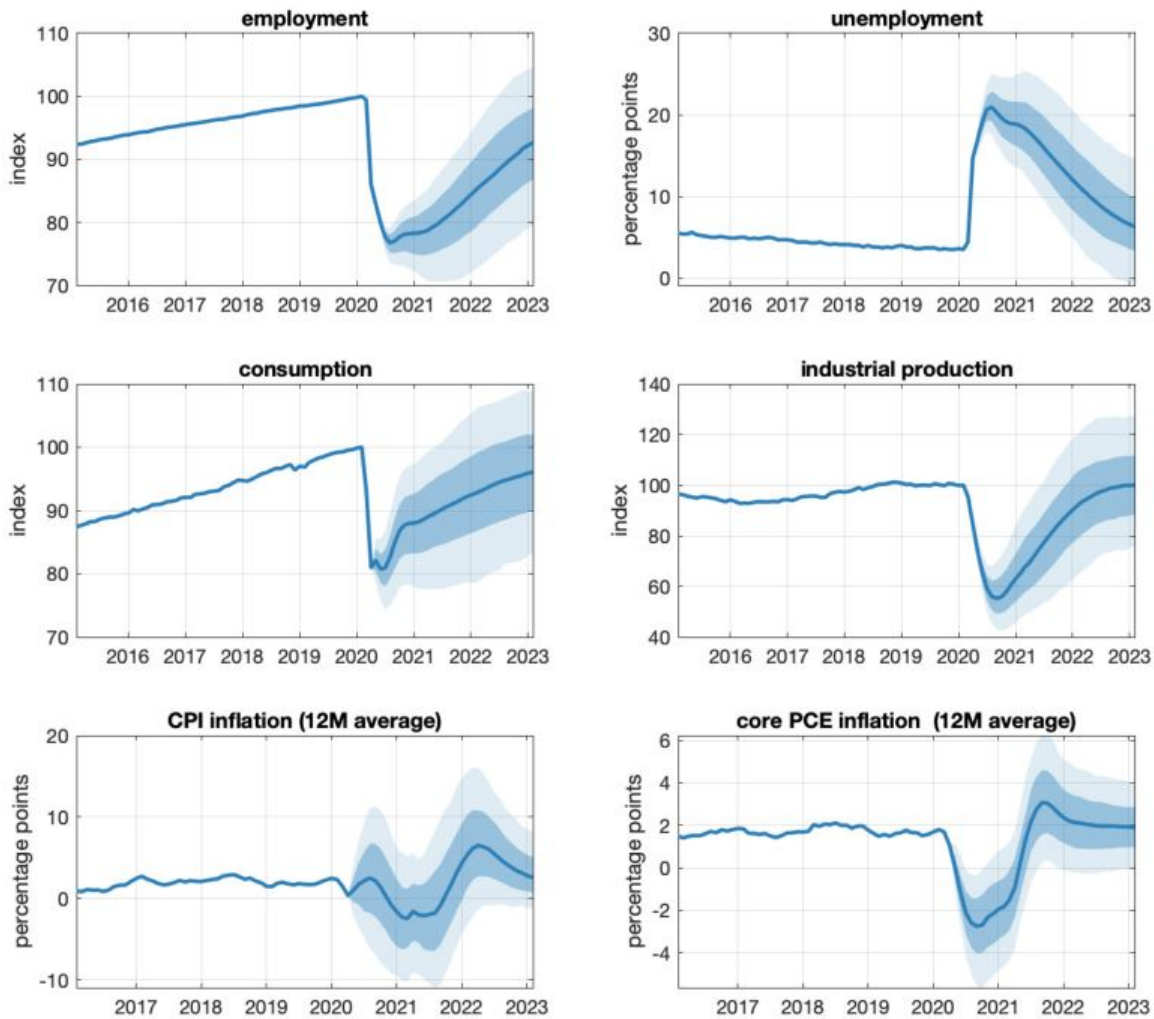


Figure 4: Figure 2 from [Primiceri and Tambalotti \(2020\)](#). Forecasts from April 2020 under baseline scenario for v_t , 68% and 95% bands.

95% forecast error bands do not include the rapid rebound in unemployment and consumption that we have seen since the early weeks of the pandemic. Allowing for the widely discussed possibility of the COVID-19 shock having a more transitory effect than previous recessions (i.e., G closer to 0 than B) would have widened the error bands, providing a quantitative forecast that more accurately reflected the debate at the time of the forecast and one that is ex post more accurate.

3.2 Additional Information in the Data

Whereas the approaches above keep the same variables but modify the model, the next two approaches seek to utilize recent and past data to improve forecasts. We emphasize that the ability to leverage information in the data depends on valid assumptions about the comovement of variables.

3.2.1 Learning from Higher Frequency Data

Given how rapidly the effects of the pandemic were felt and how swiftly policymakers have had to respond, it has been crucial to incorporate high frequency data to ensure that we are using all available information for our forecasts. To that end, several papers have used mixed-frequency (MF) models for forecasting. In the context of (1), these papers allow for the econometrician to only observe X_t or averages of X_t in particular periods, which provides the possibility of incorporating data of different frequencies in X_t (e.g., monthly industrial production and quarterly GDP). Intuitively, the joint behavior of X_t allows us to infer the values of unobserved elements of X_t . During the pandemic, it was reasonable to expect that these joint distributions might have evolved (i.e., B and C in equation (1) changed). Without accounting for these changes, one may draw misleading conclusions from the high frequency data.

An illustration of the role of high frequency data in informing forecasts is provided by [Schorfheide and Song \(2020\)](#), who present real-time macroeconomic forecasts during the pandemic using a relatively standard model from [Schorfheide and Song \(2015\)](#). They include three quarterly series (GDP, investment, and government expenditures) and eight monthly series (unemployment rate, hours worked, Consumer Price Index, industrial production, Personal Consumption Expenditure, Federal Funds Rate, 10-year Treasury Bond Yield, and S&P 500 Index). For the results we will discuss, the underlying parameters B and C are estimated using data available on January 31, 2020, and forecasts are updated purely from new information about the realized path of the data rather than changes in parameter values.⁶

We find mixed success comparing the realizations of the 2020Q2 data to what is forecast by the model using data available on June 30, 2020. By this time, the quarter had come to an end, but the GDP numbers had not yet been announced. GDP fell to 10% below the 2019Q4 level, close to the [Schorfheide and Song \(2020\)](#) median forecast of 12% and within the 60% predictive bands. On the other hand, 2020Q2 investment fell 9% relative to 2019Q4, substantially less than the June 30 median forecast of 22% and even the 95% quantile of 16%. Note that the quantiles already capture the inherent relative volatility of the respective series, with the error bands for investment double the width of those for GDP.

The fact that the GDP nowcast (i.e., the forecast of current quarter GDP before it has been reported) performs so well relative to the investment nowcast suggests a change in the relationship between the monthly and quarterly variables. This is a similar issue to that raised in our discussion of [Lenza and Primiceri \(2020\)](#) and [Primiceri and Tambalotti \(2020\)](#)—there were features of the data during the pandemic that we might have expected *ex ante* to have changed, but the model forecasts did not take these into account. Economic theory suggests that investment should fall less for more transitory shocks. Given the *ex ante* likelihood that the COVID-19 recession would be more short-lived than past recessions, one might have expected that the response of investment

⁶When the data after January 2020 were used for estimation, [Schorfheide and Song \(2020\)](#) run into the challenge highlighted by [Lenza and Primiceri \(2020\)](#), as the pandemic era outliers result in unreasonable parameter estimates, leading to poor forecasts.

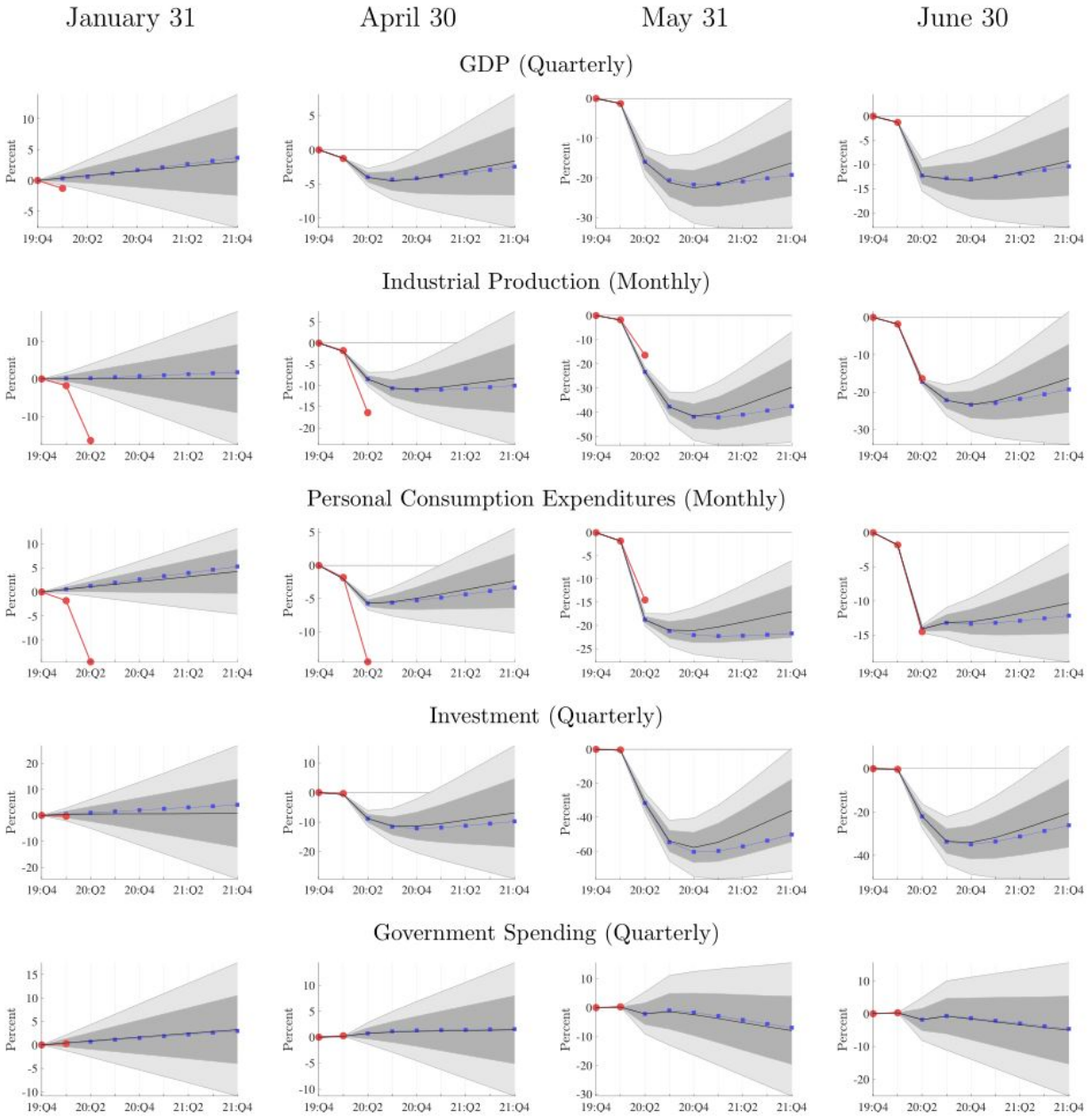


Figure 5: Figure 3 from [Schorfheide and Song \(2020\)](#). Forecasts from January 31, April 30, May 31, and June 30, 2020, realized data (solid red) and median forecast (solid black) with 60% and 90% bands. Solid blue line represents point forecasts obtained by fixing the federal funds rate at 5 basis points. All variables are plotted relative to their 2019Q4 levels.

relative to the movement in the monthly series would be muted.

The forecasts updated dramatically as monthly data is observed during the initial decline of economic activity between April to June. On April 30, May 31, and June 30, [Schorfheide and Song \(2020\)](#) forecast 2020Q2 GDP of 4%, 15%, and 12% below the 2019Q4 level, respectively. These updates are large not only relative to past data, but also relative to the error bands of the forecasts. Moreover, none of these updates are arising from changes in the underlying parameters. To justify such large updates, one needs to interpret the shocks in May and June as being extremely low probability events given the April 30 data. Given the uniqueness of the period, the plausibility of such an interpretation depends on subjective judgement.

[Koop et al. \(2021\)](#) study a similar model and ask how allowing for different forms of time-varying volatility, in the spirit of [Lenza and Primiceri \(2020\)](#), affects nowcasts for GDP. While the point nowcasts do not differ substantially, time-varying volatility leads to larger nowcast error bands. In addition, imposing time-invariant variances leads to a more rapid update of the nowcasts as high frequency data are observed. Given the short sample, evaluating which of these nowcasts are preferred requires subjective judgement.

An alternative to increasing the time series dimension through high frequency data is to focus on the cross section studying panel data. For example, [Aaronson et al. \(2020\)](#) and [Larson and Sinclair \(2021\)](#) find some success using the panel of U.S. states (together with data on Google Trends and state of emergency declarations) to improve nowcasts of unemployment insurance (UI) claims.

3.2.2 Learning from Past Crises

One response to the shortcomings in [Schorfheide and Song \(2020\)](#) is to ask if there are historical episodes that can suggest where our current estimated model might make errors. To that end, [Forni et al. \(2020\)](#) adjust forecasts from various MF models using information from the Great Recession. The class of models used can be viewed as minor modifications of (1).⁷ In what follows, we reference our benchmark VAR model (1) instead of the actual models in [Forni et al. \(2020\)](#) in order to economize on notation and simplify the exposition.

First, they compute *similarity adjusted* forecasts in which they increase the weight on observations from the Great Recession. The reweighting captures the idea that the COVID-19 economy is more similar to the Great Recession than the average time period. In the notation of (1), this changes the estimates of B and C to be closer to the values that best fit the Great Recession period.

Second, they produce *intercept adjusted* forecasts by correcting forecasts based on forecast errors made during the Great Recession. The correction accounts for systematic bias that may occur during recessions. Formally, rather than take $B^h X_t$ as the h -period-ahead forecast, they use $B^h X_t + u_{t^*}$, where u_{t^*} is the forecast error from the corresponding period in the Great Recession.

[Forni et al. \(2020\)](#) generate forecasts using data available in April 2020, which includes monthly

⁷More precisely, [Forni et al. \(2020\)](#) consider $y_{t+h} = \sum_{k=0}^K \beta_k y_{t-k} + \sum_{l=0}^L \delta_l x_{t-l} + \sum_{m=0}^M \gamma_m u_{t-m}$, where y_t is the variable of interest, x_t contains additional predictors, and u_t captures the forecast error. The variety of models involve different assumptions on β_k and δ_l as well as different methods of estimation.

observations for the beginning of the pandemic but only includes quarterly data through 2019Q4. They focus on quarterly forecasts of GDP and investment but include monthly data on industrial production, employment, or the VIX as additional predictors. They consider a range of models that differ based on the number of lags included and assumptions about the parameters.

The forecast error correction substantially changes the forecasts but the reweighting of observations does not.⁸ However, with the benefit of hindsight, we see that the model substantially underpredicts the initial decline in GDP but overpredicts the persistence of the decline in GDP growth, with forecast annualized declines of approximately 10% and 5% in 2020Q2 and 2020Q3, respectively, in contrast to the 33% decline and 38% increase in the data. [Feroni et al. \(2020\)](#) forecast a decline in investment that had a trough level close to the data but overpredict the persistence of this decline. Their forecasts are roughly in line with the [Schorfheide and Song \(2020\)](#) April 2020 forecasts. Like [Schorfheide and Song \(2020\)](#), [Feroni et al. \(2020\)](#) overpredict the decline of investment relative to GDP as they fail to acknowledge the differences in the COVID-19 recession. Instead of using the Great Recession, [Ludvigson et al. \(2021\)](#) use data on past natural disasters to predict the economic effects of the COVID-19 pandemic. They also find mixed success depending on the variable, performing relatively well for industrial production but poorly for initial claims and service sector employment. Similarly, [Aaronson et al. \(2020\)](#) use the comovement between UI claims and Google Trends during recent hurricanes in the U.S. to forecast UI claims during the pandemic.

The forecast errors in [Feroni et al. \(2020\)](#) are unsurprising ex post but might also be expected ex ante. The COVID-19 recession has been larger, more rapid, and less persistent than the Great Recession. These differences were considered distinct and even likely possibilities in March. In principle, one could have used the results from [Feroni et al. \(2020\)](#) as bounds for forecasts, assuming a belief about how the COVID-19 recession would evolve relative to the Great Recession. For conditional forecasting, [Feroni et al. \(2020\)](#) also provide a way to generate plausible bounds on the paths of variables that we choose to condition our forecasts on. More generally, even though we may perceive clear differences between the current situation and previous recessions, knowing the direction of these differences can allow us to productively incorporate past experience to refine our forecasts.

4 Looking Back at What Changed

While the literature above focused on forecasting the economy real time during the pandemic, it is useful to look back on data that we now have, both economic and epidemiological, to understand what assumptions turned out to be valid. [Ng \(2021\)](#) provides one perspective on this question.

The paper incorporates COVID-19 epidemiological data and provides insight into two questions:

1. Controlling for COVID-19 data, did the structure of the economy change?

⁸These results are consistent with [Stock and Watson \(2012\)](#) who, using a different model, find that the evolution of the macroeconomic variables during the Great Recession was due to large shocks rather than structural changes in the economy.

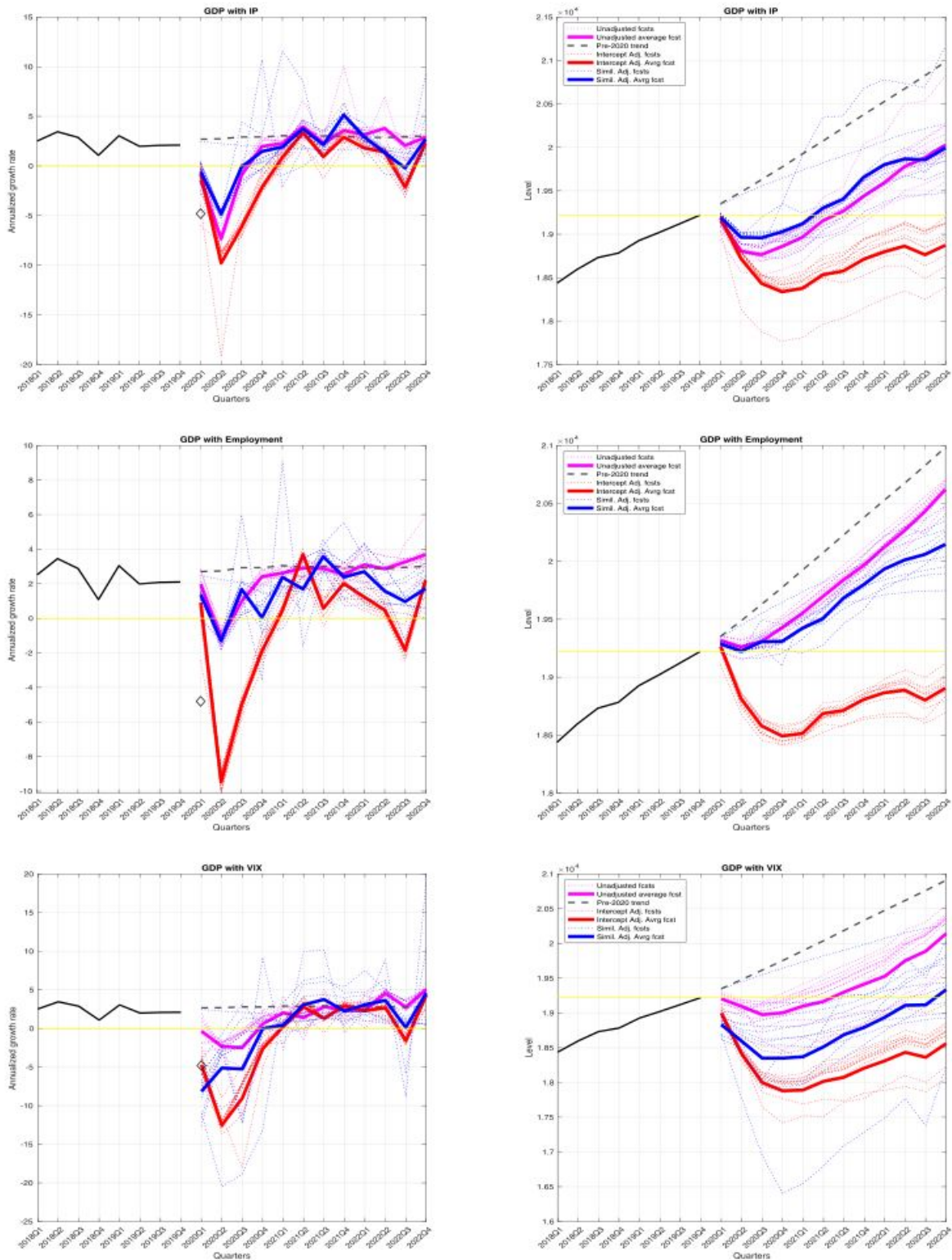


Figure 6: Figure 6 from Forni et al. (2020). Forecasts for GDP, unadjusted (magenta), intercept adjusted (red), and similarity adjusted (blue). Solid lines average across models, dotted lines indicate individual models.

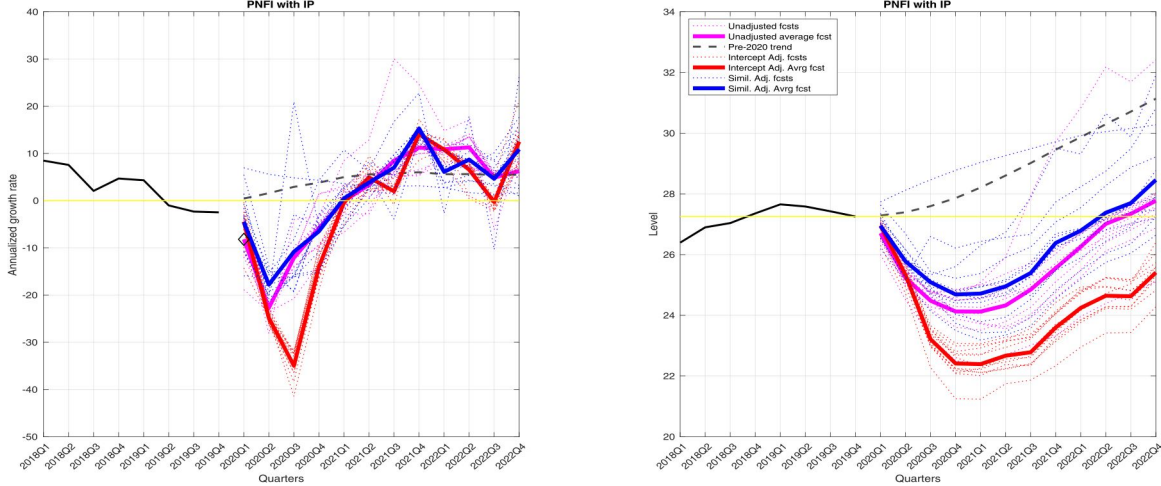


Figure 7: Figure 10 from [Forni et al. \(2020\)](#). Forecasts for investment, unadjusted (magenta), intercept adjusted (red), and similarity adjusted (blue). Solid lines average across models, dotted lines indicate individual models.

2. Controlling for COVID-19 data, how volatile were the data?

The paper is also an example of how epidemiological data can be easily incorporated into our econometric models. While this may have been harder to accomplish early in the pandemic, we now have sufficient data to inform our estimates.

For the question on the structure of the economy, [Ng \(2021\)](#) estimates the factor model:

$$X_t = HF_t + \alpha z_t + u_t, \quad (4)$$

where X_t is a large panel of over one hundred macroeconomic and financial indicators, F_t is a small number of unobserved factors that account for the comovement in X_t , and z_t is a moving average of the growth in either COVID-19 cases or COVID-19 hospitalizations. The COVID-19 variable z_t is set to zero before the pandemic. She estimates (4) using data through February 2020, and then data through December 2020. If z_t fully captures all the changes in the comovement of the different variables, then the coefficients H and estimated factors \hat{F}_t will not be substantially affected by the inclusion of 2020 data. As we have discussed in Section 3, the stability of relationship between macroeconomic variables is a critical issue for econometricians to confront.

[Ng \(2021\)](#) finds that the factors do not change substantially. In particular, Figure 8 shows three different estimates for the first macroeconomic factor—one using data through February 2020 and two using data through December 2020 with COVID-19 hospitalization or case data. The three lines overlap almost perfectly. [Ng \(2021\)](#) reports that for the other factors (not plotted), the estimates with data through December 2020 have a correlation of at least 0.65. The correlation is close to one for about half the factors. These high correlations suggest that changes in the comovement in the economy during the pandemic can mostly be explained by COVID-19 data. It is somewhat surprising that simply incorporating COVID-19 data can reverse the result in [Lenza](#)

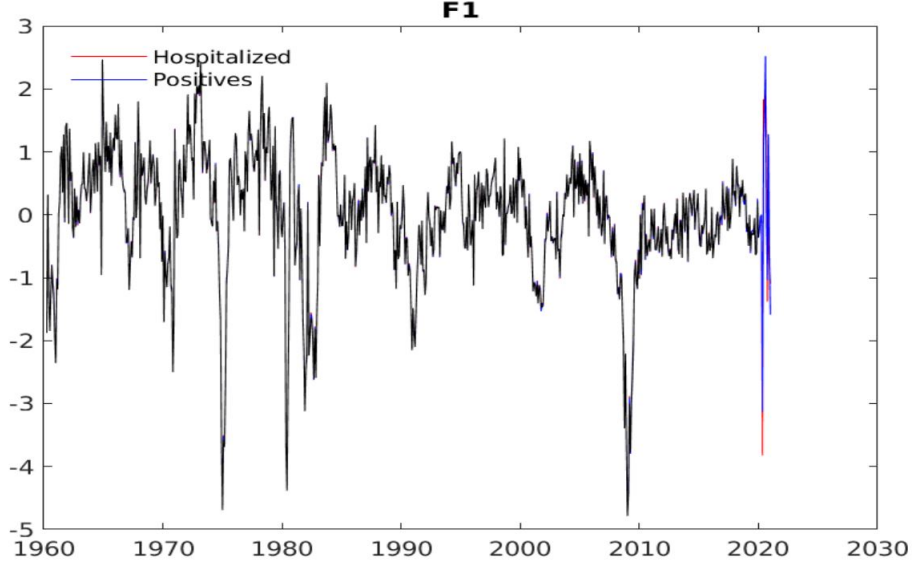


Figure 8: Figure 2 from Ng (2021). First macroeconomic factor estimated using data through February 2020 (black) and using data through December 2020 with hospitalization (red) or case (blue) data.

and Primiceri (2020) that the pandemic era macroeconomic data can severely impact parameter estimates. It suggests, for instance, that the COVID-19 variable z_t can capture much of the change in the fluctuations of GDP and investment relative to other variables in the economy, which we highlighted in our discussion of Schorfheide and Song (2020) and Foroni et al. (2020).

On the question of volatility, Ng (2021) estimates the following model:

$$x_{i,t+h} = \beta_i^{(h)} \hat{F}_t + \gamma_{i,h} Z_t + v_{i,t+h}^{(h)}, \quad (5)$$

where $x_{i,t+h}$ is one of the data series, \hat{F}_t are the factors estimated from (4), Z_t are the moving averages of the growth in COVID-19 cases and hospitalizations, and $v_{i,t+h}^{(h)}$ are h -period-ahead forecast errors. For each period t and a given horizon h , she computes an “uncertainty index” based on Jurado et al. (2015) by averaging the variances of the $v_{i,t+h}$ across the various series.

This uncertainty index provides a measure of the volatility of the shocks (both idiosyncratic and common) in the economy. Recall that in Section 3, the change in volatility was the only change considered by Lenza and Primiceri (2020). On the other hand, Primiceri and Tambalotti (2020) assumed that the traditional macroeconomic shocks were negligible in March and April, but at historical levels of volatility subsequently. The estimated coefficients $\gamma_{i,h}$ in equation (5) allow us to test for evidence of a new shock. Assuming Z_t captures the COVID-19 shock, the uncertainty index is a measure of whether volatility was particularly high compared to historical episodes.

Figure 9 shows that the uncertainty index reaches approximately the level of the 1973-74, 1981-82, and 2007-09 periods. In other words, while the level of volatility was high by historical standards, it was not unprecedented. It is important, however, to note that the uncertainty index

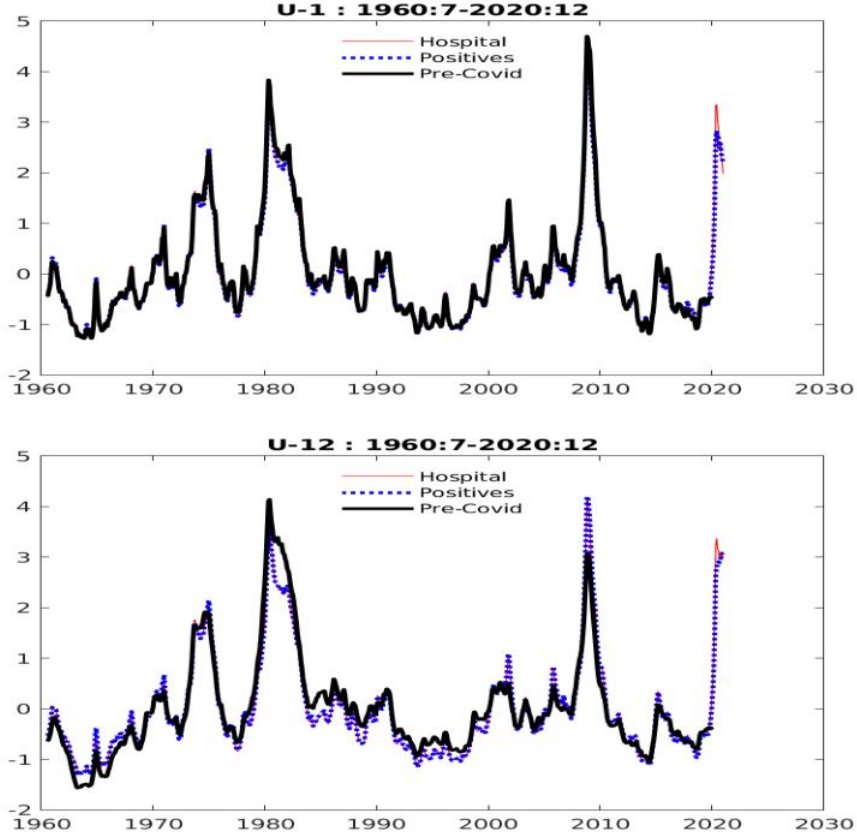


Figure 9: Figure 4 from Ng (2021). Uncertainty index estimated using data through February 2020 (black) and using data through December 2020 with hospitalization (red) or case (blue) data. **Top panel:** one-month-ahead forecasts (i.e., $h = 1$); **Bottom panel:** twelve-month-ahead forecasts (i.e., $h = 12$).

is designed to capture *shock volatility* rather than *parameter uncertainty* since the parameters are estimated using the full data sample through December 2020. In particular, at the early stages of the pandemic, we did not have the data needed to obtain precise estimates of $\gamma_{i,h}$ in equation (5) or α in equation (4). As a result, if we were estimating the same models real time, there would be a substantially larger amount of parameter uncertainty to deal with, which should imply larger error bands in one's real-time forecasts.

Ng (2021) finds that the coefficients $\gamma_{i,h}$ on the COVID-19 data in equation (5) are important for predicting $x_{i,t+h}$. The relevance of the COVID-19 data emphasizes the new significance of epidemiological data in determining macroeconomic fluctuations, even after accounting for the factors \hat{F}_t . This supports the interpretation by Primiceri and Tambalotti (2020) of COVID-19 introducing a new shock to the economy. The importance is further emphasized by contrasting the results in Ng (2021) with those in Carriero et al. (2021b), who estimate a time-varying volatility VAR without including COVID-19 data and find historic increases in their measures of volatility. For instance, in their benchmark model, Carriero et al. (2021b) report peak macroeconomic uncertainty level of 7.6, about three times the Great Recession peak.

An important caveat in the results is that the data X_t used by [Ng \(2021\)](#) are cleaned to fit the factor structure. First, the data are demeaned, with different means for data before and after March 2020. Second, a dummy is included for March 2020 that absorbs the initial large variation. The results should be interpreted as capturing the variation around these two different means after ignoring the initial large impact rather than the full extent of fluctuations.

5 Conclusion

When forecasting in the absence of precedent, one needs to tap on information outside one's typical models to construct informative forecasts. We have illustrated approaches of using external knowledge or new data sources that the literature has discussed. As we look back on the successes and failures of the various forecasts, we find that a greater acknowledgement of the particular circumstances of the pandemic could have led to more accurate forecasts. As an econometrician, one has to balance feasibility, transparency, and sophistication in one's models. As a consumer of these forecasts, one has to then interpret each forecast in the context of the assumptions. However, until the assumptions have been modeled probabilistically, it is difficult to know what quantitative adjustment one should make to one's forecasts to account for changes in the economy.

With hindsight, one can analyze which assumptions turned out to be valid. However, this is not straightforward even after the event. For instance, while [Sims and Zha \(2006\)](#) argue that the Great Moderation is best explained by a reduction in volatility, [Primiceri \(2006\)](#) and [Sargent et al. \(2006\)](#) argue that the decline in inflation should be explained by policymakers learning and adapting policy. A similar debate is found in [Stock and Watson \(2012\)](#) and the accompanying discussion. The difficulty in establishing what changed in the economy ex post emphasizes the substantial role for parameter uncertainty in the middle of an unprecedented episode.

While this essay has used the COVID-19 pandemic as a case study, the themes apply to other rare events and even normal times. Assumptions often mask uncertainty and bias forecasts. Additional data is informative insofar as it is appropriately modeled. Models should have the flexibility for parameter estimates to adjust probabilistically to incoming data, and forecasters should transparently communicate limitations in this learning process.

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