Crawford School of Public Policy

CAMA

Centre for Applied Macroeconomic Analysis

Nowcasting 'True' Monthly US GDP During the Pandemic

CAMA Working Paper 14/2021
January 2021

Gary Koop
University of Strathclyde
Economic Statistics Centre of Excellence

Stuart McIntyre
University of Strathclyde
Economic Statistics Centre of Excellence

James Mitchell
Federal Reserve Bank of Cleveland
Economic Statistics Centre of Excellence
Centre for Applied Macroeconomic Analysis, ANU

Aubrey Poon
University of Strathclyde
Economic Statistics Centre of Excellence
Centre for Applied Macroeconomic Analysis, ANU

Abstract

Expenditure side and income side GDP are both measured at the quarterly frequency in the US and contain measurement error. They are noisy proxies of `true' GDP. Several econometric methods exist for producing estimates of true GDP which reconcile these noisy estimates. Recently, the authors of this paper developed a mixed frequency reconciliation model which produces monthly estimates of true GDP. In the present paper, we investigate whether this model continues to work well in the face of the extreme observations that occurred during the pandemic year of 2020 and consider several extensions of it. These extensions include stochastic volatility and error distributions that are fat tailed or explicitly allow for outliers. We also investigate the performance of conditional forecasting, where we estimate our models using data through 2019 and then use these to nowcast throughout 2020. Nowcasts are updated each month of 2020 conditionally on the new data releases which occur each month, but the parameters are not re-estimated. In total we compare the real-time performance of 12 nowcasting approaches over the pandemic months. We find that our original model with Normal homoskedastic errors produces point nowcasts as good or better than any of the other approaches. A property of Normal homoskedastic models that is often considered bad (i.e. that they are not robust to outliers), actually benefits the KMMP model as it reacts confidently to the rapidly evolving economic data. In terms of nowcast densities, we find many of the extensions lead to larger predictive variances reflecting the great uncertainty of the pandemic months.

Keywords

Pandemic, Nowcasting, Income, Expenditure, Mixed frequency model, Vector Autoregression, Bayesian

JEL Classification

Address for correspondence:

(E) cama.admin@anu.edu.au

ISSN 2206-0332

Nowcasting ‘True’ Monthly US GDP During the Pandemic*

Gary Koop[1,3], Stuart McIntyre[1,3], James Mitchell[2,3,4], and Aubrey Poon[1,3,4]

[1]University of Strathclyde
[2]Federal Reserve Bank of Cleveland
[3]Economic Statistics Centre of Excellence
[4]Centre for Applied Macroeconomic Analysis

January 25, 2021

Abstract

Expenditure side and income side GDP are both measured at the quarterly frequency in the US and contain measurement error. They are noisy proxies of ‘true’ GDP. Several econometric methods exist for producing estimates of true GDP which reconcile these noisy estimates. Recently, the authors of this paper developed a mixed frequency reconciliation model which produces monthly estimates of true GDP. In the present paper, we investigate whether this model continues to work well in the face of the extreme observations that occurred during the pandemic year of 2020 and consider several extensions of it. These extensions include stochastic volatility and error distributions that are fat tailed or explicitly allow for outliers. We also investigate the performance of conditional forecasting, where we estimate our models using data through 2019 and then use these to nowcast throughout 2020. Nowcasts are updated each month of 2020 conditionally on the new data releases which occur each month, but the parameters are not re-estimated. In total we compare the real-time performance of 12 nowcasting approaches over the pandemic months. We find that our original model with Normal homoskedastic errors produces point nowcasts as good or better than any of the other approaches. A property of Normal homoskedastic models that is often considered *bad* (i.e. that they are not robust to outliers), actually benefits the KMMP model as it reacts confidently to the rapidly evolving economic data. In terms of nowcast densities, we find many of the extensions lead to larger predictive variances reflecting the great uncertainty of the pandemic months.

Keywords: Pandemic; Nowcasting; Income; Expenditure; Mixed frequency model; Vector autoregression; Bayesian

*Portions of this research were conducted under independent contract for the Federal Reserve Bank of Cleveland; the views expressed herein are those of the authors and not necessarily those of the Federal Reserve Bank of Cleveland or the Federal Reserve System. We would like to thank Ana Galvao, Kevin Lee, Massimiliano Marcellino, Ivan Petrella and other participants at the National Institute of Economic and Social Research workshop ‘The Impact of the Covid-19 Pandemic on Macroeconomic Forecasting’ for constructive comments on this work.

1 Introduction

The Covid-19 pandemic poses serious challenges to the macroeconomic forecaster using time series methods. The extreme values of many macroeconomic variables which occurred in the pandemic raise questions about the validity of standard time series models. For instance, will a model estimated using data from more economically stable times be appropriate for forecasting in pandemic times? When a pandemic observation on a predictor occurs which is far beyond the range of values observed in past data, is it valid to extrapolate forecasts beyond this range? Will the extreme observations occurring in the pandemic contaminate parameter estimates in our time series models, leading to poor forecast performance now and in the future? These are the questions which motivate the present paper. In it, we investigate how a particular econometric model, the Mixed Frequency Vector Autoregression (MF-VAR) of Koop, McIntyre, Mitchell and Poon (2020, hereafter KMMP) which is used to produce reconciled estimates of US GDP growth, performs during the pandemic and whether it can be improved.

The goal of the MF-VAR of KMMP was to produce historical estimates and nowcasts of real Gross Domestic Product (GDP) in the US at the monthly frequency using quarterly data on two estimates of GDP produced by the Bureau of Economic Analysis (BEA) using the expenditure side (GDP_E) and income side (GDP_I) approaches to the measurement of GDP. Theoretically, GDP_E and GDP_I should be the same as one another. In practice, they can diverge substantially due to measurement error. This divergence can have an impact on macroeconomic forecasting and policy analysis (see, for instance, Nalewaik, 2010, 2012). This has led to the development of several econometric models for reconciling the GDP_E and GDP_I numbers so as to produce an estimate of true GDP. The reconciliation model of Aruoba, Diebold, Nalewaik, Schorfheide and Song (2016) is an influential one which is used to produce the Federal Reserve Bank of Philadelphia's popular reconciled quarterly measure of true real GDP: GDPplus.[1] The MF-VAR of KMMP builds the structure of Aruoba et al. (2016) into an MF-VAR involving many monthly predictors so as to successfully produce reconciled estimates of true GDP at the monthly frequency.

In this paper, we investigate how the MF-VAR of KMMP nowcasts during the pandemic in real time and consider many extensions of it which may be better at modeling the extreme observations on many variables in 2020. These extensions involve various ways of modeling the error distribution. The model of KMMP assumed these errors to be Normal and homoskedastic. We consider several extensions which relax these two assumptions. The former is relaxed through consideration of models with fat tailed error distributions and distributions which explicitly model outliers. The latter is relaxed by allowing for the errors to have stochastic volatility. We present nowcasts of all models in a real time nowcasting exercise for the pan-

[1] See `https://www.philadelphiafed.org/research-and-data/real-time-center/gdpplus`.

demic months. We then repeat the analysis using a conditional forecasting method where all models' parameters are estimated using data through 2019, and conditional forecasting is then done throughout 2020 where nowcasts are updated conditional on the new data releases which occur each month.

Remember that the general pattern of US economic growth in 2020 was that it was slightly negative in the first quarter, very negative in the second and very positive in the third as the economy began to rebound. We compare our different nowcasting approaches in terms of how quickly and how accurately their nowcasts captured this pattern. In terms of point forecasts, we find that the original model of KMMP nowcasts at least as well as other approaches. But the other approaches often led to larger predictive variances which may be an accurate reflection of the great uncertainty in the pandemic months.

2 The MF-VAR of KMMP

The MF-VAR of KMMP builds the measurement error perspective of Aruoba, Diebold, Nalewaik, Schorfheide and Song (2016) into a mixed frequency model so as to produce monthly estimates of true GDP.[2] GDP_E and GDP_I provide a great deal of information about what true GDP is at the quarterly frequency, but provide no information about how it fluctuates within the quarter. Accordingly, KMMP include many additional monthly predictors so as to increase the amount of monthly information available to pin down the month-by-month movements in true GDP.

A monthly-quarterly MF-VAR can be written as:

$$Ay_t = By_{t-1} + \epsilon_t, \epsilon_t \sim N(0, \Sigma), \tag{1}$$

where $t = 1, \ldots, T$ is time at the monthly frequency, y_t is a vector of dependent variables. Some of the variables are only observed at the quarterly frequency and, for these, they appear in y_t as unobserved monthly values. A is lower triangular and Σ is diagonal.[3] The MF-VAR is a state space model where the unobserved monthly values of the quarterly variables are treated as latent states. The state space model is completed by including measurement equations which link the unobserved monthly variables to their quarterly counter-parts (i.e. imposing restrictions which reflect the fact that GDP for the three months in a quarter will

[2]By measurement error perspective, Aruoba et al (2016) mean that the model incorporates the assumption that true GDP equals GDP_E (or GDP_I) plus an error. Thus, the error in their econometric model is purely measurement error (or noise) in GDP_E (or GDP_I) which contains no information useful for predicting true GDP. An implication of this assumption is that the variance of true GDP is less than that of GDP_E (or GDP_I).

[3]Note that writing the MF-VAR in structural form does not restrict the reduced form error covariance matrix. There are substantial computational advantages to writing the model in this form since the fact that Σ is diagonal means estimation can be done one equation at a time.

sum to the quarterly quantity).

The main model of Aruoba et al. (2016) involves a vector of dependent variables $y_t = (U_t, GDP_t, GDP_{Et}, GDP_{It})'$, where U_t is the quarterly unemployment rate which is used as an instrument to identify the model.[4] One of the models in KMMP uses this same vector of dependent variables, except at the monthly frequency. Since GDP_t, GDP_{Et} and GDP_{It} are not observed at the monthly frequency, they enter as latent states in the MF-VAR as in KMMP. However, U_t is observed at the monthly frequency. KMMP show that the measurement error perspective can be embedded into the MF-VAR by restricting:

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 \\ 0 & -1 & 1 & 0 \\ 0 & a_{42} & -1-a_{42} & 1 \end{bmatrix} \tag{2}$$

and

$$B = \begin{bmatrix} b_{11} & b_{12} & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}. \tag{3}$$

This is the basic structure of the model of KMMP. KMMP's empirical work (and the empirical work in the present paper) also includes additional monthly variables in the MF-VAR. But since they simply enter the model in the same manner as U_t, we will not include them to keep the notation simple.

The MF-VAR is a state space model and standard econometric methods exist for estimation and prediction. Bayesian inference and prediction in the MF-VAR can be done by choosing a prior and using Markov Chain Monte Carlo (MCMC) methods. These are described in KMMP.

3 Extensions of KMMP for Pandemic Nowcasting

Several attempts have been made to extend homoskedastic MF-VARs and VARs to improve their forecast performance during the pandemic. In this section, we will briefly summarise a few of the themes which occur in a few relevant papers.[5] Then we will suggest a few extensions of the MF-VAR of KMMP inspired by these themes.

[4] Aruoba et al (2016) justify this identification assumption by arguing that unemployment is constructed using household surveys whereas GDP measures are independently constructed using business surveys and, thus, the measurement errors in each should be independent of one another.

[5] Rossi (2020) provides general guidance on how to evaluate and improve forecasts in the presence of instabilities.

Schorfheide and Song (2020) is an update of Schorfheide and Song (2015). The latter was a pioneering MF-VAR paper that assumed homoskedastic Normal errors. The former paper found this MF-VAR to nowcast poorly during the pandemic in a real time exercise. However, an alternative strategy worked much better. This was one where the parameters of the MF-VAR were not updated in real time (i.e. the parameters were estimated using data through 2019 and remained at these estimates as new data were released through the months of 2020). This raised the possibility that the extreme observations which occurred in the pandemic months of 2020 were contaminating the parameter estimates leading to poor nowcast performance. We will use this strategy as one of the approaches in our empirical work and refer to it as "conditional nowcasting". That is, all our nowcasts produced using this approach will use a model estimated on data through 2019 but then the monthly nowcasts will condition on the newly released data each month.

Another recent contribution is Lenza and Primiceri (2020). This paper uses a VAR instead of an MF-VAR. It extends the standard homoskedastic model by assuming a mixture distribution for the errors which allows the error variance to increase by a large amount when the pandemic hits. We quote one of their conclusions: "Our results show that the ad-hoc strategy of dropping these observations may be acceptable for the purpose of parameter estimation. However, disregarding these recent data is inappropriate for forecasting the future evolution of the economy, because it vastly underestimates uncertainty." This quotation highlights two themes which we will investigate in our empirical work: i) that incorporating exteme pandemic observations could have a negative impact on parameter estimates, and ii), that it may be reasonable for nowcasts to exhibit large predictive variances due to the great uncertainty that the pandemic has caused.

Several other recent contributions have developed models which allow for the pandemic to be considered an outlier or large variance shock. The treatment of the error variance is a key component in papers such as Antolin-Diaz, Drechsel and Petrella (2020) and Carriero, Clark, Marcellino and Mertens (2020). However, the treatment of the error variance differs between the two papers. In the former paper it follows a mixture distribution, whereas in the latter stochastic volatility is key. But these papers share the idea that the model must allow for the error variance to increase during the pandemic period to downplay the effect of outlier observations. The idea that the pandemic period is somehow an outlier also appears in the non-parametric MF-VAR approach of Huber, Koop, Onorante, Pfarrhofer and Schreiner (2020).

These considerations motivate our adding a variety of extensions on to the model of KMMP. In relation to the error distribution, a class of different specifications can be obtained if we relax the assumption that the errors in the i^{th} equation of the MF-VAR, $\epsilon_{i,t}$, are homoskedastic and replace them with the assumption that

$$\epsilon_{i,t} \sim N(0, \lambda_{i,t} e^{h_{i,t}}). \tag{4}$$

Different assumptions about $\lambda_{i,t}$ and $h_{i,t}$ define a wide range of different error distributions (see, e.g., Chan and Hsiao, 2014).

A conventional stochastic volatility (SV) model is obtained if we assume $\lambda_{i,t} = 1$ and

$$h_{i,t} = h_{i,t-1} + v_{i,t}, v_{i,t} \sim N(0, \sigma^2_{h_{i,t}}). \tag{5}$$

If we assume $h_{i,t}$ to be constant but

$$\lambda_{i,t} | \nu_i \sim IG(\nu_i/2, \nu_i/2) \tag{6}$$

then the errors have a Student-t distribution with ν_i degrees of freedom, thus allowing for heavier tails than the Normal. We refer to models involving this assumption as fat tailed.

If we assume $h_{i,t}$ to be constant but

$$\begin{cases} \lambda_{i,t} \sim U(2,10) \text{ with probability of } & p \\ \lambda_{i,t} = 1 \text{ with probability of } & 1-p \end{cases} \tag{7}$$

then we have a specification of the form used in Stock and Watson (2016) which allows for outliers. We refer to this specification as an 'outlier model'.

Furthermore we can add SV to the fat tailed model or outlier model obtaining models that allow for both extreme errors and serial dependence in the volatility process.

In summary, we have two treatments of serial dependence in the volatility process (i.e. homoskedasticity and SV) and three types of distribution for the errors (i.e. Normal, fat tailed and outlier). Considering every combination of these leads to six different models. These models range from the original model of KMMP (homoskedasticity and Normal errors) through a conventional SV specification (SV plus Normal errors) similar to Carriero, Clark, Marcellino and Mertens (2020) through outlier specifications (no SV but outlier error distribution) such as that used by Lenza and Primiceri (2020) through the SV plus outlier errors specification (SVO) of Stock and Watson (2016) and the fat-tailed plus SV specification of Antolin-Diaz, Drechsel and Petrella (2020). We consider all six combinations in our empirical work.

For each of these six specifications, we carry out our nowcasting exercise in two ways. The first is a standard real time exercise where the models are estimated on an expanding window of data and parameter estimates are updated to reflect new data releases. The second is conditional nowcasting, where all model parameters are estimated using data through the end of 2019. Throughout the months of 2020, the nowcasts are updated to reflect new data releases, but the parameter estimates are not updated.

Details of all these models and the Bayesian methods we use for estimating and nowcasting with them are given in the Technical Appendix.

4 The Data

The data were obtained from the Federal Reserve Bank of St. Louis' FRED-MD and ALFRED databases. Our quarterly variables are GDP_E and GDP_I. Our monthly variables include unemployment, hours worked, the consumer price index, the industrial production index, personal consumption expenditure (PCE), the Federal Funds rate, the 10 year Treasury bond yield and the S&P 500 index. These variables can be expected to have predictive ability for GDP and are precisely the ones used in Schorfheide and Song (2015).[6]

Aruoba et al. (2016) argue that measurement errors are best modeled as *iid* in growth rates rather than in levels and, in this paper, we follow this practice. With the exceptions of the unemployment rate, the Federal Fund rate and Treasury bond yield, all variables are log differenced. The unemployment rate is logged and the interest rate variables are untransformed.

Our data runs from 1960q1/1960m1 through November 2020. In November 2020, data through 2020Q3 was available for GDP_E, but we only had data through 2020Q2 for GDP_I. For the monthly variables, we had data through October. Our empirical work is all done in real time and respects the release calendar. So, for instance, nowcasts made at the end of May 2020 use the vintage of data available at that time.

5 How does the MF-VAR of KMMP Deal with Pandemic Observations?

5.1 Design of the Nowcasting Exercise

The MF-VAR of KMMP was found to produce reliable historical estimates and nowcasts of monthly GDP through 2019. But the question arises as to whether it will continue to do so during the pandemic. To address this question, we begin by carrying out a real time nowcasting[7] exercise for 2020 comparing the Normal homoskedastic model of KMMP to its various extensions.

[6] Recent work has assessed whether there are additional gains to consideration of weekly or even daily indicators, including from private sector sources, on top of the publicly available monthly indicator data used in this paper. Lewis, Mertens and Stock (2020) and Carriero, Clark and Marcellino (2020) demonstrate the utility of weekly economic data during the 2020 pandemic.

[7] We will use the terminology *nowcast* throughout, even though some of what what we produce are forecasts and some backcasts.

We undertake a fixed event nowcasting exercise for four events: 2020Q1,...,2020Q4. The goal is to nowcast true GDP for these four quarters. We produce up to 11 nowcasts for each of these events. Our initial nowcast uses information available near the end of December 2019 (denoted "Dec-19 Data Vintage"). By 'near the end of' we mean in the last week of the month. Specifically, we wait until the latest quarterly estimates of GDP_E and GDP_I have been published by the BEA, which is typically in this last week of the month, before producing density nowcasts based on this information and information known at this point in the month about the other variables in the MF-VAR. We then repeat the exercise on a month-by-month basis through the October 2020 Data Vintage. We produce nowcasts each month until the initial release of both GDP_E and GDP_I has occurred. GDP_E has a release delay of approximately one month, GDP_I a release delay of approximately two months. So, for instance, by the end of August the BEA's initial releases of GDP_E and GDP_I for 2020Q2 will both have occurred. Thus we produce nine nowcasts of true GDP in 2020Q2, one based on data available near the end of December 2019 and one for each of the 8 months in 2020 through August.

Of course, we have no realizations of true GDP to which we can compare our nowcasts. To aid in interpretation, note that (at the time of writing) the current vintage annualized estimates for 2020Q1, Q2 and Q3 for the quarterly growth in GDP_E are -5.08%, -37.66% and 28.58%. For GDP_I, the first two quarters are -2.56% and -40.85% while the third quarter has not been released. Using data available near the end of 2019, all the nowcasts for 2020 were for moderately positive growth. In reality, 2020Q1 ended up having mildly negative growth, 2020Q2 was severely negative growth and 2020Q3 was a strong bounce back. The question we keep in mind when interpreting results is how quickly and how well a model discovered these unexpected (from the point of view of December 2019) extreme observations.

Our model also produces nowcasts of monthly GDP_E and GDP_I. In the interests of brevity, these are not presented in this paper. Their properties are very similar to those for true GDP and are available on request from the authors.

5.2 Results of the Nowcasting Exercise

We present our results one quarter at a time. For each quarter, we present four tables. Each table compares results for the three different error distributions (Normal, fat tails and outlier). The four tables arise since we have two treatments of stochastic volatility (with and without) and two treatments of coefficient estimation (real time estimation and estimation using data available at the end of 2019 - 'conditional nowcasting') and we consider every combination of these cases. Thus we have 12 different approaches. We illustrate the shape of the density nowcasts produced by each approach for each quarter of 2020 by extracting, and then tabulating, their first four moments. We do so as data accumulate - the "Data Vintages" are updated - through the months of 2020. To be clear when looking at the Tables, the "Dec-19 Data Vintage", for example, refers to when the density nowcast is produced: the relevant MF-VAR model is estimated using data as available in the last week of December 2019.

5.2.1 Nowcasting 2020Q1

Tables 1, 2, 3 and 4 summarize the properties of our nowcast densities for 2020Q1. This quarter is of less interest than later quarters in the pandemic, since the pandemic had little or no impact on the first two months of the quarter. Nevertheless, it allows us to compare the performance of our various approaches in times that are more normal.

Consider first the point nowcasts. These are similar across all 12 of our approaches. All are initially nowcasting slightly positive growth until April. At the end of April, the initial release of GDP_E, of roughly minus five percent, occurs and the nowcasts of true GDP immediately drop to be near this value. We posit that this is due to the measurement error perspective built into all our models. That is, all models have an equation which says true GDP is GDP_E plus error which binds true GDP closely with GDP_E (and GDP_I.

Turning to higher order predictive moments, these also tend to be quite similar across our 12 approaches. When working with these largely pre-pandemic data sets, the risk of parameter estimation being contaminated with outliers is very low and results are basically the same regardless of whether estimation is done in real time or using 2019 data. Similarly, the inclusion or not of stochastic volatility has little impact. The only notable difference across approaches is that the KMMP-outliers (i.e. SVO) model tends to produce nowcasts with larger kurtosis (and slightly higher predictive standard deviations and skewness) than any of the other models.

Data Vintage	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis
	KMMP				**KMMP-fat tails**				**KMMP-outliers**			
Dec-19	2.95	6.74	-0.01	3.06	2.95	6.80	-0.02	4.18	2.93	10.64	0.13	17.79
Jan-20	2.33	5.19	0.02	3.05	2.28	4.89	-0.02	4.59	2.37	7.83	1.37	21.57
Feb-20	1.33	4.28	0.00	3.07	1.00	4.24	0.00	3.94	1.03	7.10	0.14	29.24
Mar-20	5.80	5.27	0.04	3.10	1.57	4.31	0.05	3.65	2.34	5.10	0.35	7.08
Apr-20	-2.68	1.39	0.11	3.14	-4.01	0.90	0.03	3.19	-3.11	1.16	-0.05	3.11
May-20	-4.68	0.01	-0.07	4.38	-4.79	0.00	0.23	4.08	-4.66	0.02	0.53	3.41

Table 1: Properties of GDP predictive densities for 2020Q1: Models without stochastic volatility, parameters estimated in real time

Data Vintage	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis
	KMMP				**KMMP-fat tails**				**KMMP-outliers**			
Dec-19	2.95	6.74	-0.01	3.06	2.95	6.80	-0.02	4.18	2.93	10.64	0.13	17.79
Jan-20	2.35	5.24	0.03	3.01	2.36	4.92	0.07	4.19	2.35	7.88	-0.03	16.13
Feb-20	1.36	4.27	-0.03	3.07	1.04	4.39	-0.02	4.35	1.08	7.08	-0.19	21.92
Mar-20	6.80	5.20	-0.01	3.11	1.62	4.85	0.06	3.79	2.46	5.77	0.19	8.61
Apr-20	-1.13	1.86	0.04	3.28	-3.86	1.13	0.00	3.02	-3.27	1.13	0.05	3.12
May-20	-4.72	0.01	1.73	15.04	-4.75	0.01	-0.19	5.54	-4.78	0.03	-1.37	15.70

Table 2: Properties of GDP predictive densities for 2020Q1: Models without stochastic volatility, parameters estimated using data through 2019 ('conditional nowcasting')

Data Vintage	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis
	KMMP-SV				**KMMP-SV-fat tails**				**KMMP-SV-outliers**			
Dec-19	2.91	5.50	0.01	3.07	2.93	5.80	0.06	3.83	2.90	8.54	-0.02	13.98
Jan-20	2.20	4.20	0.02	3.14	2.21	4.18	0.03	3.75	2.26	7.29	0.70	42.55
Feb-20	0.88	3.60	-0.03	3.06	0.81	3.75	-0.11	3.79	0.96	6.47	0.09	26.31
Mar-20	1.86	3.40	0.00	3.18	1.73	3.58	0.06	3.88	1.71	4.34	0.45	8.67
Apr-20	-5.15	1.94	0.01	2.96	-3.32	1.20	-0.04	2.95	-3.51	2.69	-0.60	3.58
May-20	-4.73	0.02	0.35	3.55	-4.69	0.01	0.04	4.05	-4.73	0.01	0.93	8.52

Table 3: Properties of GDP predictive densities for 2020Q1: Models include stochastic volatility, parameters estimated in real time

Data Vintage	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis
	KMMP-SV				**KMMP-SV-fat tails**				**KMMP-SV-outliers**			
Dec-19	2.91	5.50	0.01	3.07	2.93	5.80	0.06	3.83	2.90	8.54	-0.02	13.98
Jan-20	2.29	4.41	0.03	2.99	2.23	4.48	0.06	3.78	2.26	5.44	0.71	19.39
Feb-20	1.06	3.72	0.00	3.02	0.96	4.01	-0.03	3.79	0.97	5.84	0.43	29.78
Mar-20	1.92	4.06	0.05	3.12	1.77	4.48	-0.05	3.52	1.73	5.72	-0.10	9.11
Apr-20	-5.45	2.03	-0.13	3.23	-3.62	1.41	0.02	3.20	-4.11	1.08	-0.16	3.28
May-20	-4.69	0.01	1.21	6.67	-4.68	0.01	0.43	4.85	-4.78	0.00	0.04	4.29

Table 4: Properties of GDP predictive densities for 2020Q1: Models include stochastic volatility, parameters estimated using data through 2019 ('conditional nowcasting')

5.2.2 Nowcasting 2020Q2

The second quarter of 2020 was the worst for the economy, as the severe lockdowns produced record breaking falls in economic output. Both GDP_E and GDP_I eventually signalled drops of around 40% in this quarter. Tables 5, 6, 7 and 8 allow us to assess how quickly and accurately our different approaches to nowcasting reacted to this.

Consider first the results of the model of KMMP in Table 5. In the first few, pre-pandemic, months of the year the model was nowcasting positive growth. In March, the nowcast is revised down to being slightly negative (-0.36%). By the end of March, the financial variables such as the stock price were signalling problems for the economy, but the macroeconomic variables such as the unemployment rate and industrial production were not yet signalling problems, due to their backward-looking nature and release delays. By the end of April (with the initial release of GDP_E for 2020Q1, as well as poor monthly values for many of the monthly variables being released) the model of KMMP is producing a point nowcast of strong negative growth of minus 20%. But it is only by the May data vintage and subsequent months that the point nowcasts move to the region of minus 40% , which is close to the eventual realizations of GDP_E and GDP_I. May is an important month, since this is when a particularly extreme observation occurs: the unemployment rate went up by 250% in April. This information was released in May and hence forms part of the May 2020 data vintage. The model of KMMP captured this negative signal well and lowered its point nowcast to extremely negative GDP growth.

The preceding paragraph discussed the point nowcasts. The predictive variances are quite large in May and June and only become small at the end of July when the initial release of 2020Q2 GDP_E occurs. We would argue this is sensible and illustrates a pattern found throughout our results. The model of KMMP is reacting well to the information in the monthly variables in terms of the point nowcasts. But information signalled in them is not sufficient to reduce the great uncertainty in pandemic times and this is reflected in large predictive variances. It is only when information on one of the GDP proxies is released that the uncertainty in the nowcasts is vastly reduced. This reflects the measurement error perspective embedded in this model which strongly links contemporaneous values of true GDP to GDP_E and GDP_I.

We next discuss whether any of the other approaches does better than the model of KMMP. Overall, our 12 different approaches tend to produce similar nowcasts. But there are a few places where they differ somewhat and it is these differences we will discuss here. If we focus on the crucial months of April, May and June, then a pattern (with some exceptions) is that adding stochastic volatility, fat tails or a mixture distribution tends to lead to larger predictive variances and often larger kurtosis (but only rarely are we finding evidence of skewness and where we do it is associated with the outlier model). As one example, consider the June 2020 nowcasts from the fat-tailed model in Table 5. The point nowcast -16.70% is substantially worse than the -32.66% point nowcast of the KMMP model when considered against the realizations of 2020Q2 GDP_E and GDP_I. However, the fat-tailed model is producing a predictive variance which is over six times as large as that produced by KMMP. A similar pattern is observed with the outlier model. Adding stochastic volatility also tends to lead to much larger predictive variances, particularly in months such as June.

June 2020 is an interesting month since by the end of this month it is known that the 2020Q1 outcomes of GDP_E and GDP_I were slightly negative, many of the monthly variables for April were signaling extremely bad outcomes, but some of the monthly variables were recovering in May from the new lows set in April. In the face of these conflicting signals, models with non-Normal errors and/or stochastic volatility tended to be highly uncertain in the nowcasts they produce and this is reflected in large predictive standard deviations in key months. Possibly this is an accurate reflection of the great uncertainty of those pandemic months and, thus, one can argue that these extensions of KMMP are warranted. However, it is the case that for 2020Q2 KMMP produced predictive densities that more quickly allocated more weight to the extreme negative economic growth which actually occurred in 2020Q2.

Data Vintage	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis
	KMMP				**KMMP-fat tails**				**KMMP-outliers**			
Dec-19	2.52	8.30	-0.01	3.00	2.53	8.26	0.01	4.06	2.43	13.08	0.13	16.91
Jan-20	2.48	8.07	0.01	2.99	2.59	7.26	0.01	3.97	2.52	11.40	0.13	16.75
Feb-20	2.33	7.61	-0.01	3.02	2.37	6.82	0.00	3.86	2.41	12.42	0.24	28.09
Mar-20	-0.36	7.62	0.00	3.00	-0.93	16.25	-0.18	5.82	-1.13	13.97	-0.01	16.21
Apr-20	-20.16	14.04	-0.02	2.99	-19.00	28.51	-0.40	4.63	-18.32	25.17	-1.12	11.39
May-20	-39.52	32.70	0.14	3.14	-29.03	25.15	-0.12	3.26	-33.95	64.95	-0.43	3.85
Jun-20	-32.66	15.49	0.26	3.33	-16.70	91.84	1.03	3.43	-21.15	73.72	0.15	4.08
Jul-20	-38.95	1.64	0.15	3.09	-36.91	2.60	0.17	2.91	-37.55	2.47	0.30	3.19
Aug-20	-39.27	0.02	0.12	4.15	-39.03	0.01	0.12	4.89	-39.25	0.04	-1.01	9.88

Table 5: Properties of GDP predictive densities for 2020Q2: Models without stochastic volatility, parameters estimated in real time

Data Vintage	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis
	KMMP				**KMMP-fat tails**				**KMMP-outliers**			
Dec-19	2.52	8.30	-0.01	3.00	2.53	8.26	0.01	4.06	2.43	13.08	0.13	16.91
Jan-20	2.51	7.99	0.00	2.99	2.65	7.53	-0.01	4.25	2.59	12.24	-0.15	25.40
Feb-20	2.37	7.59	-0.01	3.05	2.46	6.88	-0.04	4.17	2.45	12.95	-0.65	24.34
Mar-20	-0.54	7.56	0.02	3.00	-0.93	18.52	0.07	4.97	-1.25	16.00	0.25	26.94
Apr-20	-18.04	11.80	0.04	3.07	-20.02	41.87	-0.37	4.29	-18.95	26.75	-1.42	13.08
May-20	-35.72	18.34	-0.02	3.00	-29.76	30.47	-0.15	3.46	-34.80	72.19	-0.10	2.44
Jun-20	-26.78	10.64	-0.02	3.00	-16.29	63.93	0.65	3.69	-12.16	219.03	0.17	2.55
Jul-20	-32.74	3.43	0.27	3.15	-37.13	2.57	0.42	3.53	-37.72	2.84	0.25	3.43
Aug-20	-39.18	0.02	0.41	6.91	-39.17	0.03	-0.07	6.35	-39.08	0.06	1.58	22.34

Table 6: Properties of GDP predictive densities for 2020Q2: Models without stochastic volatility, parameters estimated using data through 2019 ('conditional nowcasting')

Data Vintage	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis
	KMMP-SV				**KMMP-SV-fat tails**				**KMMP-SV-outliers**			
Dec-19	2.59	6.52	0.01	3.11	2.64	6.98	-0.01	3.76	2.58	10.23	0.00	16.43
Jan-20	2.53	6.13	-0.01	3.09	2.54	6.09	0.09	3.90	2.65	9.88	1.01	30.12
Feb-20	2.11	5.91	0.00	3.11	2.14	5.94	-0.01	3.55	2.24	10.10	0.27	21.06
Mar-20	0.60	8.34	-0.04	3.25	0.39	10.10	-0.06	4.65	0.37	15.56	-0.03	13.74
Apr-20	-15.35	22.24	0.16	3.73	-16.77	23.28	-0.22	3.50	-17.81	41.16	-0.64	10.27
May-20	-14.29	20.28	0.02	3.04	-25.90	26.16	-0.06	3.20	-29.07	60.27	-0.64	5.80
Jun-20	-167.52	3200.84	-0.54	4.88	-12.45	125.95	1.03	3.20	-19.85	102.76	0.73	5.46
Jul-20	-36.06	3.51	0.44	3.42	-36.47	2.99	0.18	2.92	-36.94	3.33	0.25	3.04
Aug-20	-39.15	0.02	-0.42	2.66	-39.20	0.02	-0.11	2.77	-39.20	0.03	-0.02	4.33

Table 7: Properties of GDP predictive densities for 2020Q2: Models include stochastic volatility, parameters estimated in real time

Data Vintage	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis
	KMMP-SV				**KMMP-SV-fat tails**				**KMMP-SV-outliers**			
Dec-19	2.59	6.52	0.01	3.11	2.64	6.98	-0.01	3.76	2.58	10.23	0.00	16.43
Jan-20	2.60	6.26	0.01	3.08	2.63	6.42	0.01	3.83	2.57	8.95	0.71	28.08
Feb-20	2.33	6.16	-0.01	2.97	2.30	6.20	-0.07	4.22	2.38	9.65	0.27	26.83
Mar-20	0.77	9.88	0.00	3.44	0.48	12.28	-0.02	4.64	0.48	21.26	-0.57	11.47
Apr-20	-17.00	27.98	0.27	3.93	-16.97	34.62	-0.18	3.79	-17.16	58.66	-0.54	7.81
May-20	-40.54	125.04	-0.95	4.48	-27.06	30.57	-0.10	3.29	-30.97	60.09	-0.68	4.30
Jun-20	-24.88	23.53	-0.16	3.42	-8.73	226.53	0.33	1.79	-5.36	236.68	-0.26	2.47
Jul-20	-36.43	3.07	0.16	3.04	-36.68	3.14	0.33	3.13	-37.62	2.68	0.40	3.32
Aug-20	-39.24	0.02	-0.14	4.98	-39.30	0.02	-0.24	4.10	-39.08	0.02	-0.06	3.54

Table 8: Properties of GDP predictive densities for 2020Q2: Models include stochastic volatility, parameters estimated using data through 2019 ('conditional nowcasting')

5.2.3 Nowcasting 2020Q3

The third quarter of 2020 saw GDP_E and GDP_I partially bounce back after the collapse of 2020Q2. Tables 9, 10, 11 and 12 reveal a consistent pattern for all our 12 models. In April, May and June all models were missing the bounce back and still nowcasting negative growth for 2020Q3, but subsequently the nowcasts turn positive until by the end of October (when the initial release of GDP_E for 2020Q3 of almost 30% growth arrived) strong positive growth was nowcast.

But within this general pattern, there are some differences between the various approaches. Consider the point forecasts which, with the exception of the basic KMMP model, all show nowcasts of 2020Q3 growth in single digits until the end of October. In contrast, the homoskedastic model of KMMP was nowcasting 14% growth by the end of August. Its point nowcasts identified the upturn faster than the other models. As for the 2020Q2 results, we are finding that the alternative models which add stochastic volatility, fat tails or accommodate outliers, tend to produce predictive variances which are larger than the homoskedastic model of KMMP. This increase in uncertainty could be taken as a desirable property in the context of the information available in the summer of 2020. Until the end of October, the information available to the models was the fact that GDP_E and GDP_I had collapsed in 2020Q2 plus information in the monthly variables. The former was a bad signal and the latter a good signal for the economy in Q3. In the face of such conflicting signals, it would be difficult for any time series econometric model to nowcast strong growth in 2020Q3. But KMMP is placing more weight on the good information in the monthly variables in August and September. This could be because the other approaches allow for outliers and/or increases in the error variances. These tend to downplay the information in outliers so when strong positive news was arriving via the monthly predictors in August and September, this tended to be given less weight by the other approaches. Thus, a property of Normal homoskedastic models that is often considered bad (i.e. that they are not robust to outliers), actually benefited the KMMP model in that it did not downplay the good news of August and September.

The other key difference between the Normal homoskedastic KMMP model and all the extensions of it we are considering is the same as that noted in our discussion of the 2020Q2 results. The extensions typically lead to greater uncertainty reflected in larger predictive variances. As one example of this, compare the predictive variances of the Normal homoskedastic version of KMMP with a model which is the same except that it allows for stochastic volatility (i.e. compare the KMMP results in Table 9 to the KMMP-SV results in Table 11). Predictive variances in the latter are much larger than the former.

Data Vintage	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis
	KMMP				**KMMP-fat tails**				**KMMP-outliers**			
Dec-19	2.33	8.67	0.00	3.05	2.29	9.02	0.03	4.51	2.16	14.19	0.36	19.95
Jan-20	2.38	8.59	-0.01	3.06	2.54	7.78	-0.05	4.15	2.34	12.13	-0.11	10.34
Feb-20	2.55	8.49	0.00	3.03	2.58	7.60	-0.05	4.01	2.50	14.44	0.18	21.79
Mar-20	-1.27	9.54	-0.01	3.04	-1.96	33.66	-0.59	8.18	-2.40	21.61	-0.13	9.39
Apr-20	-18.73	32.18	-0.06	3.02	-14.60	107.24	-0.20	4.23	-15.36	61.82	-0.12	4.74
May-20	-44.96	65.80	-0.22	3.14	-22.05	99.46	-0.17	4.12	-22.29	63.50	-0.27	5.43
Jun-20	-17.34	17.08	0.02	3.08	-12.24	28.53	-0.19	3.77	-15.79	33.39	0.37	12.44
Jul-20	2.35	13.60	0.14	3.07	-1.49	43.99	-0.13	4.35	-9.74	105.76	-1.18	7.91
Aug-20	14.24	12.39	-0.07	3.01	-0.85	18.46	-0.08	3.27	5.93	36.14	-0.41	6.20
Sep-20	16.38	11.36	-0.07	2.95	5.20	24.33	-0.32	3.13	-2.93	38.82	0.66	3.46
Oct-20	26.37	1.71	-0.11	3.08	26.72	1.44	-0.14	3.08	27.05	1.79	-0.18	3.34

Table 9: Properties of GDP predictive densities for 2020Q3: Models without stochastic volatility, parameters estimated in real time

Data Vintage	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis
	KMMP				**KMMP-fat tails**				**KMMP-outliers**			
Dec-19	2.33	8.67	0.00	3.05	2.29	9.02	0.03	4.51	2.16	14.19	0.36	19.95
Jan-20	2.45	8.43	-0.01	3.01	2.55	7.76	0.07	3.56	2.43	13.03	-0.05	12.98
Feb-20	2.60	8.53	-0.02	3.06	2.66	7.74	-0.05	4.12	2.62	13.46	0.79	19.39
Mar-20	-1.45	9.42	0.00	3.01	-1.92	33.84	-0.01	4.28	-2.52	23.02	0.08	10.17
Apr-20	-13.42	20.33	0.02	3.05	-15.09	129.52	-0.24	4.07	-15.95	62.07	-0.21	4.66
May-20	-20.94	22.83	-0.07	3.04	-22.64	101.79	-0.11	3.78	-22.67	53.69	-0.21	4.45
Jun-20	-12.98	14.66	0.03	3.04	-14.69	31.77	-0.14	3.72	-14.74	29.70	-0.04	9.75
Jul-20	-0.75	19.53	0.05	2.93	-5.26	39.12	-0.36	4.10	-2.94	57.47	-1.43	12.58
Aug-20	1.04	16.21	0.04	3.00	-1.85	18.16	-0.05	3.23	-2.15	24.11	0.04	5.57
Sep-20	1.52	12.31	0.10	3.08	-3.29	17.72	-0.13	3.09	-1.07	26.14	0.19	3.17
Oct-20	20.97	3.75	-0.23	3.21	27.08	2.16	0.02	3.23	26.04	3.70	-0.28	3.19

Table 10: Properties of GDP predictive densities for 2020Q3: Models without stochastic volatility, parameters estimated using data through 2019 ('conditional nowcasting')

Data Vintage	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis
	KMMP-SV				**KMMP-SV-fat tails**				**KMMP-SV-outliers**			
Dec-19	2.50	6.82	-0.02	3.05	2.49	7.42	0.02	3.78	2.45	11.14	0.53	23.24
Jan-20	2.51	6.58	-0.02	3.13	2.47	6.23	0.07	4.11	2.51	10.06	-0.55	32.17
Feb-20	2.35	6.29	0.01	3.16	2.37	6.10	-0.05	3.75	2.45	10.89	0.14	23.59
Mar-20	0.30	12.39	-0.20	4.11	0.01	14.52	-0.22	4.36	0.13	23.04	0.21	9.89
Apr-20	-6.78	47.59	-0.13	4.13	-9.36	70.57	-0.22	3.77	-8.94	108.74	-0.22	6.72
May-20	-13.18	49.75	-0.13	3.48	-18.99	109.60	-0.11	3.91	-15.85	102.83	-0.17	6.24
Jun-20	-75.15	8239.47	-0.12	5.52	-8.78	30.65	-0.12	3.66	-10.79	86.00	-0.11	10.70
Jul-20	-1.35	65.31	0.11	3.27	4.35	51.31	0.03	3.24	-0.87	116.19	-0.99	9.51
Aug-20	-1.78	41.87	-0.01	3.02	5.93	26.06	-0.10	3.22	-2.07	72.49	-0.78	8.02
Sep-20	4.51	32.13	-0.05	2.91	7.29	26.38	-0.34	3.19	0.78	64.91	-0.88	5.30
Oct-20	26.67	1.54	-0.11	3.12	26.89	1.39	-0.04	3.17	27.21	1.85	-0.11	3.27

Table 11: Properties of GDP predictive densities for 2020Q3: Models include stochastic volatility, parameters estimated in real time

Data Vintage	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis
	KMMP-SV				**KMMP-SV-fat tails**				**KMMP-SV-outliers**			
Dec-19	2.50	6.82	-0.02	3.05	2.49	7.42	0.02	3.78	2.45	11.14	0.53	23.24
Jan-20	2.56	6.43	-0.07	3.09	2.60	6.38	0.04	3.71	2.49	8.19	0.32	14.07
Feb-20	2.53	6.51	0.01	3.04	2.51	7.09	0.08	3.83	2.54	9.65	1.19	22.66
Mar-20	0.48	13.47	-0.11	3.73	0.16	17.58	-0.02	4.07	0.22	29.50	-0.18	11.66
Apr-20	-6.92	50.23	-0.08	3.75	-8.85	80.49	-0.11	3.58	-8.31	128.13	-0.32	7.14
May-20	-17.92	52.28	-0.04	3.58	-19.02	111.44	-0.08	3.68	-17.58	69.49	-0.03	4.35
Jun-20	-10.28	45.65	0.00	3.64	-10.74	41.78	-0.03	3.89	-10.61	41.32	-0.03	7.79
Jul-20	0.09	36.31	0.01	3.23	-0.67	47.60	-0.30	3.96	-0.56	70.88	-1.21	8.60
Aug-20	1.83	27.99	0.03	3.33	3.28	22.49	-0.01	3.53	3.67	26.35	0.09	5.85
Sep-20	2.69	24.57	0.01	3.25	3.95	19.54	0.05	3.25	5.09	22.99	0.09	3.66
Oct-20	25.78	2.32	-0.09	3.11	27.15	2.37	0.03	3.20	27.77	1.72	0.03	3.24

Table 12: Properties of GDP predictive densities for 2020Q3: Models include stochastic volatility, parameters estimated using data through 2019 ('conditional nowcasting')

5.2.4 Nowcasting 2020Q4

As of the time of writing, neither GDP_E nor GDP_I for 2020Q4 has been released. Tables 13, 14, 15 and 16 show how our nowcasts of these have evolved over the year as new information on the pandemic's impact on the economy became available each month. Using data through the end of October, all of our models are nowcasting positive growth for 2020Q4, but they differ substantially in how certain they are about this. That is, predictive variances differ a lot across specifications and in the same way as noted in our discussion of the nowcasts of earlier quarters. The extensions of the Normal homoskedastic model of KMMP all tend to produce larger predictive variances than the original model did. These larger predictive variances are particularly notable in models with stochastic volatility or which use mixture of distributions to model outliers, but are less noticeable for the fat tails model.

Finally, we have not offered much discussion of the comparison between models which estimate the parameters in real time and those which estimate them using data through 2019 (so-called conditional nowcasting). In contrast to what some other researchers have found, we have not found a great difference in nowcasting performance between them. We posit that this is because of the measurement error perspective built into our MF-VARs. That is, all of our models include equations which impose the restriction that true GDP equals one of its proxies plus an error. The parameters in such equations are not estimated (other than their error variances) and, thus, are not liable to be contaminated by outliers. Even though outliers potentially contaminate the estimates of the coefficients in the remainder of the MF-VAR (i.e. the equations for the monthly variables), this does not seem enough to negatively impact on our nowcasts.

Data Vintage	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis
	KMMP				**KMMP-fat tails**				**KMMP-outliers**			
Dec-19	2.25	8.90	0.01	3.06	2.27	9.21	0.07	4.28	2.06	15.28	-0.63	29.74
Jan-20	2.32	8.85	0.00	3.08	2.49	7.85	0.02	3.83	2.23	13.39	-0.12	12.63
Feb-20	2.51	8.74	0.01	3.06	2.56	7.98	0.02	4.09	2.37	13.73	-0.59	14.31
Mar-20	-0.80	9.79	-0.04	3.03	-1.54	48.38	-0.55	7.96	-2.05	26.63	0.34	9.14
Apr-20	-17.30	45.75	-0.21	3.13	-10.82	167.65	-0.09	5.23	-12.30	72.01	-0.10	4.18
May-20	-28.56	93.44	-0.43	3.41	-9.36	114.59	0.04	4.24	-9.83	73.27	-0.07	4.50
Jun-20	-14.06	23.55	-0.08	3.10	-6.01	38.93	-0.09	4.04	-8.82	37.65	-0.20	12.36
Jul-20	-11.98	21.02	0.03	3.04	-8.58	127.99	-0.40	11.87	-11.25	87.91	-0.04	8.06
Aug-20	-2.59	19.30	0.07	3.08	-3.78	18.65	0.01	3.55	-3.47	35.78	-0.10	10.63
Sep-20	-1.92	14.32	0.05	3.02	-3.39	12.08	-0.02	3.53	-5.27	19.40	-0.14	10.70
Oct-20	4.34	7.86	-0.01	3.02	4.75	7.96	0.14	4.21	3.99	32.17	1.44	13.42

Table 13: Properties of GDP predictive densities for 2020Q4: Models without stochastic volatility, parameters estimated in real time

Data Vintage	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis
	KMMP				**KMMP-fat tails**				**KMMP-outliers**			
Dec-19	2.25	8.90	0.01	3.06	2.27	9.21	0.07	4.28	2.06	15.28	-0.63	29.74
Jan-20	2.39	8.80	-0.01	3.00	2.49	8.22	0.04	3.98	2.26	15.18	-1.57	33.87
Feb-20	2.54	8.79	0.00	3.07	2.66	8.07	0.09	3.74	2.53	14.93	0.52	20.48
Mar-20	-0.89	9.58	-0.02	3.04	-1.35	46.69	0.00	4.34	-2.23	29.25	-0.23	8.14
Apr-20	-8.94	19.54	-0.04	3.09	-10.92	188.44	-0.25	4.41	-12.45	72.34	-0.07	4.59
May-20	-7.91	19.80	-0.08	3.09	-10.86	123.81	0.01	4.16	-11.65	62.87	-0.08	3.97
Jun-20	-6.57	16.81	-0.02	3.05	-9.04	48.16	-0.03	4.76	-10.08	38.64	-0.03	6.55
Jul-20	-4.70	18.25	0.08	3.06	-7.39	97.27	-0.14	4.14	-8.51	61.86	-0.05	5.57
Aug-20	-1.96	16.25	0.08	3.04	-4.28	21.65	0.03	3.40	-5.50	27.64	-0.32	7.30
Sep-20	-1.69	12.48	0.03	3.03	-3.32	13.05	0.10	3.63	-4.20	16.29	-0.27	12.84
Oct-20	4.01	7.79	0.05	3.11	0.19	19.67	2.04	15.52	23.82	421.03	0.74	3.11

Table 14: Properties of GDP predictive densities for 2020Q4: Models without stochastic volatility, parameters estimated using data through 2019 ('conditional nowcasting')

Data Vintage	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis
	KMMP-SV				**KMMP-SV-fat tails**				**KMMP-SV-outliers**			
Dec-19	2.44	7.16	-0.01	3.09	2.43	7.56	-0.04	3.58	2.43	11.54	0.14	22.97
Jan-20	2.53	6.64	-0.03	3.11	2.49	6.64	-0.02	4.04	2.48	10.00	0.83	26.45
Feb-20	2.35	6.56	0.04	3.19	2.36	6.50	-0.05	3.64	2.39	12.40	-0.27	31.69
Mar-20	0.80	14.98	-0.22	5.47	0.58	16.97	-0.02	4.03	0.68	28.77	0.01	8.02
Apr-20	-4.22	64.03	-0.19	5.20	-5.29	89.80	-0.19	4.59	-5.08	162.78	-0.68	16.73
May-20	-5.58	68.46	-0.21	3.98	-6.26	134.55	-0.11	3.91	-5.41	114.41	0.20	10.57
Jun-20	-22.89	12230.27	-0.02	6.32	-2.77	45.90	-0.25	4.53	-3.73	102.93	-0.24	10.93
Jul-20	-5.95	201.54	0.07	3.61	-3.71	168.16	-0.03	3.76	-5.38	217.27	-0.63	18.37
Aug-20	-4.97	166.43	0.09	3.65	-1.25	66.58	0.04	4.11	-4.70	138.49	-0.51	14.79
Sep-20	-3.13	110.85	0.06	3.78	-2.69	45.08	0.10	4.48	-4.52	119.74	-0.04	20.01
Oct-20	5.94	54.48	0.02	3.73	5.04	21.49	-0.03	4.06	4.30	81.47	0.55	15.61

Table 15: Properties of GDP predictive densities for 2020Q4: Models include stochastic volatility, parameters estimated in real time

Data Vintage	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis
	KMMP-SV				**KMMP-SV-fat tails**				**KMMP-SV-outliers**			
Dec-19	2.44	7.16	-0.01	3.09	2.43	7.56	-0.04	3.58	2.43	11.54	0.14	22.97
Jan-20	2.56	6.85	0.04	3.23	2.55	6.78	-0.03	3.80	2.58	8.95	-0.13	11.57
Feb-20	2.53	6.89	-0.06	3.38	2.51	7.05	0.14	4.31	2.55	10.95	0.72	25.24
Mar-20	0.99	15.31	-0.09	3.62	0.72	19.42	0.03	4.21	0.66	35.24	-0.21	9.36
Apr-20	-3.59	63.07	-0.28	4.37	-4.63	95.10	-0.14	3.97	-4.37	171.50	-0.30	14.12
May-20	-6.00	62.72	-0.21	4.52	-6.82	136.78	-0.10	4.23	-6.44	77.24	0.13	5.81
Jun-20	-4.13	68.05	-0.06	3.53	-5.00	62.52	-0.15	3.98	-4.67	59.14	0.03	12.97
Jul-20	-1.49	74.29	-0.06	3.31	-2.29	101.82	-0.02	4.09	-2.99	135.80	-0.14	5.49
Aug-20	0.83	65.30	0.11	3.45	0.19	33.11	-0.06	3.96	-0.63	39.66	0.27	7.35
Sep-20	0.83	46.45	0.06	3.34	0.27	24.35	-0.03	4.32	-0.46	34.16	0.56	10.33
Oct-20	6.90	26.44	0.10	3.13	3.74	22.06	0.46	3.98	7.23	157.53	2.74	14.13

Table 16: Properties of GDP predictive densities for 2020Q4: Models include stochastic volatility, parameters estimated using data through 2019 ('conditional nowcasting')

6 Conclusions

It is always important to provide timely and high frequency nowcasts of GDP. But, in pandemic times, it is even more important. The Normal homoskedastic MF-VAR model of Koop et al. (2020) was found to produce high quality nowcasts using data through 2019. This paper addresses the question of whether it can also produce high quality nowcasts in a time of great economic instability, and whether various extensions to the model specification improve its nowcasting performance through the pandemic.

Overall, we find that the KMMP model does a good job of doing so, reacting quickly as new information is released each month. It is especially effective at updating nowcasts in months when new releases of GDP_E and GDP_I occur. This is due to what Aruoba et al. (2016) call the measurement error perspective. It is built into the KMMP model and provides tight links between GDP and its two noisy proxies. But updates also occur using the information in the monthly predictors included in the model.

The various extensions of KMMP we tried in this paper, involving stochastic volatility and more flexible error distributions, do not improve the point nowcast performance of KMMP. A property of Normal homoskedastic models that is often considered *bad* (i.e. that they are not robust to outliers), actually benefits the KMMP model when nowcasting as it reacts confidently to the rapidly evolving economic data. The extensions do, in many cases, increase the predictive variances leading to more uncertainty about the nowcasts. This may not be helpful for the policymaker interested in precise information, but may be an accurate reflection of the uncertainty which occurred during pandemic times. As emphasized by Lerch et al. (2017), any statistical evaluation of these density nowcasts needs to be mindful of the *forecaster's dilemma*, namely that even the most skillful forecasts can be disfavored in the presence of outliers. It is important to evaluate nowcasts and forecasts over long samples, not just over periods of extreme events, although scoring rules that emphasize specific regions of the density, such as the tails, may be useful.

References

[1] Antolin-Diaz, J., Drechsel, T. and Petrella, I. (2020). Advances in nowcasting economic activity: Secular trends, large shocks and new data. Available at SSRN: https://ssrn.com/abstract=3669854 or http://dx.doi.org/10.2139/ssrn.3669854.

[2] Aruoba, S., Diebold, F., Nalewaik, J., Schorfheide, F. and Song, D. (2016). Improving GDP measurement: A measurement-error perspective. Journal of Econometrics, 191, 384-397.

[3] Carriero, A., Clark, T. and Marcellino, M. (2020). Nowcasting tail risks to economic activity with many indicators. Working Papers 202013R3, Federal Reserve Bank of Cleveland.

[4] Carriero, A., Clark, T., Marcellino, M. and Mertens, E. (2020). Measuring uncertainty and its effects in the COVID-19 era. Federal Reserve Bank of Cleveland, Working Paper No. 20-32. https://doi.org/10.26509/frbc-wp-202032.

[5] Chan, J. and Hsiao, C. (2014). Estimation of stochastic volatility models with heavy tails and serial dependence. In: I. Jeliazkov and X.-S. Yang (Eds.), Bayesian Inference in the Social Sciences, 159-180, John Wiley & Sons, Hoboken, New Jersey

[6] Huber, F., Koop, G., Onorante, L., Pfarrhofer M. and Schreiner, J. (2020). Nowcasting in a pandemic using non-parametric mixed frequency VARs. Journal of Econometrics, forthcoming.

[7] Koop, G., McIntyre, S., Mitchell, J. and Poon, A. (2020). Reconciled estimates of monthly GDP in the US. Economic Statistics Centre of Excellence (ESCoE) Discussion Papers, ESCoE DP-2020-16.

[8] Lenza, M. and Primiceri, G. (2020). How to estimate a VAR after March 2020. European Central Bank Working Paper 2461.

[9] Lerch, S., Thorarinsdottir, T., Ravazzolo, F. and Gneiting, T. (2017). Forecaster's dilemma: Extreme events and forecast evaluation. Statistical Science, 32, 106–127.

[10] Lewis, D., Mertens, K. and Stock, J. (2020). Monitoring real activity in real time: The weekly economic index. Liberty Street Economics 20200330b, Federal Reserve Bank of New York.

[11] Nalewaik, J. (2010). The income- and expenditure-side estimates of U.S. output growth. Brookings Papers on Economic Activity, 1, 71-127 (with discussion).

[12] Nalewaik, J. (2012). Estimating probabilities of recession in real time using GDP and GDI. Journal of Money, Credit and Banking, 44, 235-253.

[13] Rossi, B. (2020). Forecasting in the presence of instabilities: How do we know whether economic models work and how to improve them. CEPR Discussion Paper 14064, February 2020.

[14] Schorfheide, F. and Song, D. (2015). Real-time forecasting with a mixed-frequency VAR. Journal of Business and Economic Statistics, 33(3), 366-380.

[15] Schorfheide, F. and Song, D. (2020). Real-time forecasting with a (standard) mixed-frequency VAR during a pandemic. Federal Reserve Bank of Philadelphia Working Paper 20-26.

[16] Stock, J. and Watson, M. (2016). Core inflation and trend inflation. Review of Economics and Statistics, 98, 770-784.

Technical Appendix

The Model of KMMP

The model of KMMP (2020), which assumes the errors are homoskedastic and Normal, is defined in the paper and details of the econometrics, including priors and development of an MCMC algorithm for posterior and predictive inference, are given there. The version of the model we use is called SS(N) (Schorfheide and Song, with noise restriction imposed) in KMMP.

Adding Stochastic Volatility

We can rewrite the model of KMMP as a set of individual equations for $i = 1, ..., N$ variables as:

$$y_{i,t} = X_{i,t}\beta_i + \epsilon_{i,t}. \tag{8}$$

Stochastic volatility is present if we assume $\epsilon_{i,t} \sim N(0, e^{h_{i,t}})$ with

$$h_{i,t} = h_{i,t-1} + v_{i,t}, v_{i,t} \sim N(0, \sigma^2_{h_{i,t}}). \tag{9}$$

The priors for β_i are the same as those in KMMP and the reader is referred to our earlier paper for justification of our prior choice. The priors for the SV terms are: $h_{i,0} \sim N(0, 1)$, $\sigma^2_{h_i} \sim IG(5, .01)$ for the errors in the equations for the monthly variables. For the GDP_t equation, the priors for parameters in the SV are $h_{GDP,0} \sim N(0, 1)$, $\sigma^2_{h_{GDP}} \sim IG(10, .001)$. We do not add SV to the errors for the equations for $GDP_{E,t}$ and $GDP_{I,t}$ since these variables are latent and the latent true GDP which appears on the right hand side of these equations already has SV in it and, thus, adding SV to the errors as well would induce two SV processes in these equations. The priors for the constant error variances in these equations are σ^2_{EE}, $\sigma^2_{II} \sim IG(5, 01)$.

MCMC methods involving adding a step for drawing $h_{i,t}$ to the MCMC algorithm of KMMP. This is standard, see, for instance, Chan and Hsiao (2016).

Adding Fat Tails

The KMMP model with fat-tail SV errors is

$$y_{i,t} = X_{i,t}\beta_i + \epsilon_{i,t}, \epsilon_{i,t} \sim N(0, \lambda_{i,t}e^{h_{i,t}}), \tag{10}$$

$$\lambda_{i,t}|\nu_i \sim IG(\nu_i/2, \nu_i/2), \tag{11}$$

$$h_{i,t} = h_{i,t-1} + v_{i,t}, v_{i,t} \sim N(0, \sigma^2_{h_i}), \tag{12}$$

The priors for all parameters except ν_i are the same as those specified for the KMMP model with stochastic volatility. For the degrees of freedom parameter, we use a prior of $\nu_i \sim U(5, 50)$.

MCMC methods involving adding a step for drawing ν_i to the MCMC algorithm of the KMMP with SV model. This is standard, see, for instance, Chan and Hsiao (2016).

The version of the fat tailed model which does not have SV is the restricted special case of this model with $h_{i,t}$ replaced by h_i and given the same treatment as in KMMP.

Adding Outliers

The model which allows for outliers and SV takes the form:

$$y_{i,t} = X_{i,t}\beta_i + \epsilon_{i,t}, \epsilon_{i,t} \sim N(0, \lambda_{i,t}^2 e^{h_{i,t}}), \tag{13}$$

$$h_{i,t} = h_{i,t-1} + v_{i,t}, v_{i,t} \sim N(0, \sigma_{h_i}^2), \tag{14}$$

with

$$\begin{cases} \lambda_{i,t} \sim U(2, 10) \text{ with probability of} & p \\ \lambda_{i,t} = 1 \text{ with probability of} & 1-p \end{cases}. \tag{15}$$

The prior for $p_i \sim Beta(a_0, b_0)$, where $a_0 = \frac{1}{4m}10m$, $b_0 = (1 - \frac{1}{4m})20m$. We follow Stock and Watson (2016) and set $m = 12$ since we are working with monthly data. Other prior choices are the same as for the KMMP model with SV.

The MCMC algorithm involves the algorithm for the KMMP with SV model with extra steps for drawing the parameters relating to the outlier process. This is done by defining an indicator variable S_{it} , where $S_{it} = 1$ implies a model of $N(X_{i,t}\beta_i, \lambda_{i,t}^2 e^{h_{i,t}})$ and $S_{it} = 0$ implies a model of $N(X_{it}\beta_i, e^{h_{i,t}})$.

S_{it} can be drawn in the MCMC algorithm from the following distribution:

$$\mathbb{P}(S_{it} = 1 | y_{it}, \beta_i, h_{it}) = \frac{p_i \times \phi(y_{it}, X_{i,t}\beta_i, \lambda_{it}^2 e^{h_{it}})}{p_i \times \phi(y_{it}, X_{i,t}\beta_i, \lambda_{it}^2 e^{h_{it}}) + (1-p)\phi(y_{it}, X_{i,t}\beta_i, e^{h_{it}})}, \tag{16}$$

$$\mathbb{P}(S_{it} = 0 | y_{it}, \beta_i, h_{it}) = 1 - \mathbb{P}(S_{it} = 1 | y_{it}, \beta_i, h_{it}), \tag{17}$$

where $\phi(a, \mu, \sigma^2)$ is a Normal density with a mean μ and variance σ^2.

When $S_{it} = 1$, this implies the prior for $\lambda_{it} \sim U(2, 10)$. Then the log conditional posterior for λ_{it} is

$$p(\lambda_{it}|y_{it},\beta_i,h_{i,t}) \propto -\frac{1}{2}log(2\pi) - \frac{1}{2}log(\lambda_{it}^2 e^{h_{i,t}}) - \frac{1}{2}\frac{(y_{it}-X_{i,t}\beta_i)^2}{\lambda_{it}^2 e^{h_{it}}}, \tag{18}$$

where $2 < \lambda_{it} < 10$. To approximate this density, $p(\lambda_{it}|y_{it},\beta_i,h_{i,t})$, we use a Griddy-Gibbs sampler that bounds the support between $[2,10]$.

Lastly, the conditional posterior for p_i is $p_i|\bullet \sim Beta(a_0+T_1, b_0+T_2)$ where is T_1 is number of times in the observations $S_t = 1$ and $T_2 = T - T_1$.

The version of the fat tailed model which does not have SV is the restricted special case of this model with $h_{i,t}$ replaced by h_i and given the same treatment as in KMMP.