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20 32

Measuring Uncertainty and Its Effects in the COVID-19 Era

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We measure the effects of the COVID-19 outbreak on macroeconomic and financial uncertainty, and we assess the consequences of the latter for key economic variables. We use a large, heteroskedastic vector autoregression (VAR) in which the error volatilities share two common factors, interpreted as macro and financial uncertainty, in addition to idiosyncratic components. Macro and financial uncertainty are allowed to contemporaneously affect the macroeconomy and financial conditions, with changes in the common component of the volatilities providing contemporaneous identifying information on uncertainty. We also consider an extended version of the model, based on a latent state approach to accommodating outliers in volatility, to reduce the influence of extreme observations from the COVID period. The estimates we obtain yield very large increases in macroeconomic and financial uncertainty over the course of the COVID-19 period. These increases have contributed to the downturn in economic and financial conditions, but with both models, the contributions of uncertainty are small compared to the overall movements in many macroeconomic and financial indicators. That implies that the downturn is driven more by other dimensions of the COVID crisis than shocks to aggregate uncertainty (as measured by our method).

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1 Introduction

The extraordinary economic volatility that occurred following the COVID-19 outbreak has raised pressing questions about the magnitude of uncertainty and its effects. During this period, sources such as the Federal Open Market Committee of the Federal Reserve emphasized that uncertainty was perceived to have risen dramatically. For example, the minutes of the Committee's April 2020 meeting reported: "Participants commented that, in addition to weighing heavily on economic activity in the near term, the economic effects of the pandemic created an extraordinary amount of uncertainty and considerable risks to economic activity in the medium term." Measures of uncertainty available at high frequency — the VIX and policy uncertainty as measured by Baker, Bloom, and Davis (2016) — skyrocketed in the spring before easing up some.

Building on the immense research literature on uncertainty that emerged following the seminal work of Bloom (2009), Carriero, Clark, and Marcellino (2018) — henceforth referred to as CCM — developed an econometric model and method for jointly (1) constructing measures of macroeconomic and financial uncertainty and (2) conducting inference on uncertainty's impacts on the macroeconomy. The CCM uncertainty measures reflect common factors driving time-varying volatilities in macroeconomic and financial variables, respectively. The model is a large, heteroskedastic vector autoregression (VAR) in which the error volatilities evolve over time according to a factor structure. The volatility of each variable in the system is driven by a common component and an idiosyncratic component. Changes in the common component of the volatilities of the VAR's variables provide contemporaneous identifying information on uncertainty. Macro and financial uncertainty are allowed to contemporaneously affect the macroeconomy and financial conditions. In CCM, estimates with monthly US data for the period 1959-2014 provided substantial evidence of commonality in volatilities, with increases in macro uncertainty associated with economic recessions. Estimated impulse responses indicate that macroeconomic uncertainty has large, significant effects on real activity, but has a limited impact on financial variables, whereas financial uncertainty shocks directly impact financial variables and subsequently transmit to the macroeconomy. Although shocks to uncertainty have significant effects, estimates of historical decompositions indicate that they are not a primary driver of fluctuations in macroeconomic and financial variables. For example, over the period of the Great Recession and subsequent recovery, shocks to uncertainty made small to modest contributions to the paths of economic and financial variables, whereas shocks to the VAR's variables played a much larger role.

This paper uses the basic framework of CCM to measure changes in macroeconomic and financial

uncertainty in the US since the outbreak of the COVID-19 pandemic and to estimate uncertainty's effects. Yet, measuring uncertainty from macroeconomic and financial data in the COVID-19 period can come with some challenges. The period yielded unprecedented changes in many key variables. For example, payroll employment plummeted 14.8 percent from March to April, a decline nearly 17 times as large as the previous largest monthly decline, and employment rose 3.5 percent from May to June, an increase 3 times larger than the previous record growth rate.[1] The extremes raise questions as to whether steps should be taken to reduce the influence that the COVID observations might have on conventional estimates of time series models. Lenza and Primiceri (2020) suggest that one should do so and develop an approach to allow for temporary spikes in volatilities of innovations in an otherwise conventional Bayesian VAR (BVAR).

In this paper, in light of possible questions around how much weight to allow COVID observations to have, we consider not only the model of CCM but also a version extended to allow for temporary volatility outliers.[2] Stock and Watson (2016) developed a latent state approach to accommodating outliers in unobserved component models of inflation, and Carriero, et al. (2020) extended the approach to BVARs and showed the efficacy of the model in macroeconomic forecasting accuracy. In this paper we add outlier states to the CCM model to assess uncertainty and its effects with a specification that has the potential to reduce the influence of extreme observations from the COVID period.

The estimates we obtain yield very large increases in macroeconomic and financial uncertainty over the course of the COVID-19 period. These increases have contributed to the downturn in economic and financial conditions. Although these contributions are sizable by historical standards, they are generally dwarfed by the immense and unprecedented magnitudes of changes in some variables from March through June 2020. That is, with both models, the contributions of uncertainty are small compared to the overall movements in many macroeconomic and financial indicators. That implies that the downturn is driven more by other dimensions of the COVID crisis than shocks to aggregate uncertainty (as measured by our method).[3]

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[1] These calculations use log growth rates and data from the September 2020 vintage of FRED-MD.

[2] In unreported results, we have also considered a different, simple approach to treating the COVID observations as unusual and reducing their influence: We augmented the VAR to include dummy variables for each month of March through June 2020, with the dummy for month s having a value of 1 in month s of 2020 and 0 in all other periods. These dummies, of course, capture the variation of the COVID months and reduce their influence on the model estimates. This dummy-variable approach had mixed effects in our setting. With macro uncertainty, adding the dummies to the SVF-M model (without the outlier treatment) yields an uncertainty estimate comparable to what we get with the SVF-M-O model. But the same does not apply with financial uncertainty: The model with dummies produces an increase in uncertainty in the COVID period almost as large as the baseline SVF-M model without outlier treatment.

[3] Ludvigson, Ma, and Ng (2020) instead treat COVID as a disaster shock that causes both economic activity to

Although our two models yield very similar results in a big-picture sense, their estimates differ along some clear dimensions. Including the outlier treatment in the model mitigates the measured rise in macroeconomic and financial uncertainty and modestly reduces the estimated contributions to recent fluctuations in economic and financial indicators. The rise in uncertainty is still very large, with macroeconomic uncertainty reaching record highs and financial uncertainty rising very high, although not quite to the peaks seen in previous recessions. Notably, including the outlier treatment in the model concentrates the period of increases in uncertainty, so that the increases don't start until about the time that the pandemic actually broke out. Excluding the outlier treatment yields larger increases in measured uncertainty, such that the measures far outstrip previous record highs. However, it also results in the estimates of uncertainty rising a few or several months before the pandemic broke out. Although both sets of estimates are plausible in our judgment, we are inclined to favor the measures from the outliers-robust model over this timing consideration.

The paper is structured as follows. Sections 2, 3, and 4 present the models, data, and results, respectively. Section 5 concludes.

2 Models

In the interest of brevity, we present the version of the uncertainty model that includes the outlier volatility states. We denote this model as the BVAR-SVF-M-O specification, short for BVAR with stochastic volatility factors in the mean and outlier states added. The baseline CCM model — denoted BVAR-SVF-M — takes the same form, with the outlier states omitted.

Let y_t denote the $n \times 1$ vector of variables of interest, split into n_m macroeconomic and $n_f = n - n_m$ financial variables. Let v_t be the corresponding $n \times 1$ vector of reduced-form shocks to these variables, also split into two groups of n_m and n_f components.

Following Stock and Watson (2016) and Carriero, et al. (2020), outliers are accommodated as temporary spikes in the standard deviations of innovations to the VAR. Outliers are treated as independent over time and across variables. The outlier scale variable can take one of a grid of $N_o = 20$ values, ranging from 1 to 20. With probability $1 - p_j$, there is no outlier for variable j in period t, and the outlier scale variable $o_{j,t}$ takes a value of 1. With probability p_j, an outlier occurs, and each of the possible values of 2 through 20 has the same probability of $p_j/(N_o - 1)$. That is, outliers occur along a uniform distribution of 2 to 20.

plummet and uncertainty to rise.

With the outlier extension of CCM's model, the reduced-form shocks are:

$$v_t = A^{-1}O_t\Lambda_t^{0.5}\epsilon_t, \ \epsilon_t \sim \text{i.i.d. } N(0, I), \tag{1}$$

where A is an $n \times n$ lower triangular matrix with ones on the main diagonal, Λ_t is a diagonal matrix of volatilities, and O_t is a diagonal matrix of the i.i.d. outlier scale states (corresponding to standard deviations). The logs of the variances on the diagonal of Λ_t follow a linear factor model:

$$\ln \lambda_{jt} = \begin{cases} \beta_{m,j}\ln m_t + \ln h_{j,t}, \ j = 1, \dots, n_m \\ \beta_{f,j}\ln f_t + \ln h_{j,t}, \ j = n_m + 1, \dots, n. \end{cases} \tag{2}$$

The variables $h_{j,t}$ — which do not enter the conditional mean of the VAR, specified below — capture idiosyncratic volatility components associated with the j-th variable in the VAR, and are assumed to follow (in logs) an autoregressive process:

$$\ln h_{j,t} = \gamma_{j,0} + \gamma_{j,1}\ln h_{j,t-1} + e_{j,t}, \ j = 1, \dots, n, \tag{3}$$

with $\nu_t = (e_{1,t}, ..., e_{n,t})'$ jointly distributed as i.i.d. $N(0, \Phi_\nu)$ and independent among themselves, so that $\Phi_\nu = diag(\phi_1, ..., \phi_n)$. These shocks are also independent from the conditional errors ϵ_t.

With this setup, the reduced-form innovation variance matrix is $\Sigma_t = A^{-1}O_t\Lambda_t O_t' A^{-1\prime}$. Accordingly, the Choleski residual of each macro variable j consists of a conditionally Gaussian innovation $\epsilon_{j,t}$ that is scaled by

$$\tilde{\lambda}_{j,t}^{0.5} = o_{j,t}\lambda_{j,t}^{0.5} = o_{j,t}\sqrt{m_t^{\beta_{m,j}}h_{j,t}}.$$

The same applies for financial variables, just with the financial factor f_t replacing the macro factor m_t. As this indicates, the outlier state is idiosyncratic to each variable's volatility. Uncertainty is instead defined as the common element in volatilities, distinct from the idiosyncratic components that may have some persistence and the i.i.d. outlier scale components. This outliers-augmented version of the model adds to the baseline CCM specification an entirely transitory volatility component (the outliers), on top of the idiosyncratic stochastic volatility process that may have some persistence (and, indeed, is estimated to do so for most of the variables of the VAR).

The variable m_t is our measure of (unobservable) aggregate *macroeconomic* uncertainty, and the variable f_t is our measure of (unobservable) aggregate *financial* uncertainty. Together, the two measures of uncertainty (in logs) follow an augmented VAR process:

$$\begin{bmatrix} \ln m_t \\ \ln f_t \end{bmatrix} = D(L)\begin{bmatrix} \ln m_{t-1} \\ \ln f_{t-1} \end{bmatrix} + \begin{bmatrix} \delta_m' \\ \delta_f' \end{bmatrix}y_{t-1} + \begin{bmatrix} u_{m,t} \\ u_{f,t} \end{bmatrix}, \tag{4}$$

where $D(L)$ is a lag-matrix polynomial of order d. The shocks to the uncertainty factors $u_{m,t}$ and $u_{f,t}$ are independent from the shocks to the idiosyncratic volatilities $e_{j,t}$ and the conditional errors

ϵ_t, and they are jointly normal with mean 0 and variance $\mathrm{var}(u_t) = \mathrm{var}((u_{m,t}, u_{f,t})') = \Phi_u = \begin{bmatrix} \phi_{n+1} & 0 \\ 0 & \phi_{n+2} \end{bmatrix}$. The specification in (4) implies that the uncertainty factors depend on their own past values as well as the previous values of the variables in the model, and therefore they respond to business cycle fluctuations. Importantly, financial uncertainty affects macro uncertainty and vice-versa.

For identification, we fix the factor innovation variances and impose (using an accept/reject step in the Gibbs sampler) sign restrictions on the factor loadings so that $\beta_{m,1} > 0$ and $\beta_{f,n_m+1} > 0$.[4] In addition, we deliberately include the block restrictions of factor loadings in the volatilities specification of (2) in order to allow the comovement between uncertainties captured in the VAR structure. Conceptually, these block restrictions are consistent with broad definitions of uncertainty: Macro uncertainty is the common factor in the error variances of macro variables, and financial uncertainty is the common factor in the error variances of financial variables. However, these uncertainties may move together due to correlated innovations to the uncertainties, the VAR dynamics of uncertainty captured in $D(L)$, and responses to past fluctuations in macro and financial variables (y_{t-1}).

The uncertainty variables m_t and f_t can also affect the levels of the macro and financial variables contained in y_t, contemporaneously and with lags. In particular, y_t is assumed to follow:

$$y_t = \Pi(L)y_{t-1} + \Pi_m(L)\ln m_t + \Pi_f(L)\ln f_t + v_t, \tag{5}$$

where k denotes the number of y_t lags in the VAR, $\Pi(L) = \Pi_1 - \Pi_2 L - \cdots - \Pi_k L^{k-1}$, with Π_i an $n \times n$ matrix, $i = 1, ..., k$, and $\Pi_m(L)$ and $\Pi_f(L)$ are $n \times 1$ lag-matrix polynomials of order k_m and k_f. This model allows the business cycle to respond to movements in uncertainty, both through the conditional variances (contemporaneously, via movements in v_t) and through the conditional means (contemporaneously and with lag, via the coefficients collected in $\Pi_m(L)$ and $\Pi_f(L)$).

Note that, as a general matter of identification, our modeling strategy separates the total variance of the residual $Av_t = O_t \Lambda_t^{0.5} \epsilon_t$ into four orthogonal components: a common component, an idiosyncratic component that may have some serial correlation, an i.i.d. outlier scale component, and a component due to the conditionally independent shock ϵ_t. When a large residual shock (represented by $O_t \Lambda_t^{0.5} \epsilon_t$) hits the economy, we let the data distinguish whether this is a large

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[4]We fix the factor innovation variances at $\phi_{n+1} = 0.015$ and $\phi_{n+2} = 0.075$, similar to the original estimates of CCM. Note that, for identification, CCM instead fixed the factor loadings $\beta_{m,1}$ and β_{f,n_m+1} at values of 1 and estimated the variance-covariance matrix of innovations to the log uncertainty factors. Although the choice between the identification schemes didn't make a difference in model estimates obtained with data samples ending before the COVID period, it does matter with the extreme observations of the COVID period. For the current sample, using the normalization approach of CCM yields implausibly extreme movements in uncertainty. Using the approach we have adopted in this paper avoids such extremes while matching up well with the estimates of CCM in the period through 2014.

shock in the conditional error ϵ_t (so an outlier in a standard normal distribution, with a variance that is not moving) or rather a relatively ordinary draw for the conditional shock ϵ_t that is, however, scaled up by an increase in variance, which may be transitory or persistent, as well as common or idiosyncratic, as captured by the various components contained in $O_t\Lambda_t^{0.5}$.

In implementation with monthly data, we set the VAR lag order at $k = 6$, the lag order for the uncertainty factors in the VAR's conditional mean (k_m and k_f) at 2, and the lag order of the bivariate VAR in the uncertainty factors (d) to 2.

We estimate the model using an MCMC sampler; see CCM for details. Here we briefly explain the extension to the version of the model with outlier volatility states. The algorithm includes all of the same steps given in CCM, with adjustments to reflect the outlier states on top of the λ and h terms. Including the outliers requires two additional steps. One of these draws the outlier states from their posterior given the draw of the outlier probabilities; this step proceeds analogously to the sampling of the mixture states needed with the Kim, Shephard, and Chib (1998) approach to the idiosyncratic volatility states h. The other draws the outlier probability for each variable from a (conditional posterior) beta distribution conditional on the draws of the time series of outlier states. All results in the paper are based on 5,000 retained draws, obtained by sampling a total of 30,000 draws, discarding the first 5,000, and retaining every 5th draw of the post-burn sample.

In unreported results, we also considered an alternative approach to our outlier specification: adding the fat-tails specification of Jacquier, Polson, and Rossi (2004) to the BVAR-SVF-M model. In this alternative model, we replace the Gaussian VAR residuals ϵ_t with t-distributed shocks. In this case, the reduced-form innovation to the VAR continues to be expressed as $v_t = A^{-1}O_t\Lambda_t^{0.5}\epsilon_t$, with O_t being a diagonal matrix of i.i.d. latent states. Compared to the BVAR-SVF-M-O specification, the version with t-distributed errors differs in that the diagonal elements of O_t, $o_{j,t}$, have inverse-gamma distributions.[5] As noted in Carriero, et al. (2020), in both the SV-O and SV-t cases, the density for the outlier state $o_{j,t}$ peaks at (SV-O) or near (SV-t) 1, with a fat right-hand tail. In the SVO case, there is equal probability on outlier states between 2 and 20, whereas the SV-t case assigns most probability on values close to 1, albeit with some minimal measure placed also on values far above 20. Also, while the outlier states in the SVO case cannot take values below 1, the SV-t case assigns considerable mass also to values below one. While we regard the SV-O and SV-t approaches as comparable, the SV-O approach for which we present results is more geared toward generating sizable outliers at a variable j-specific probability of occurrence p_j that

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[5]Specifically, let $d_j/o_{j,t} \sim \chi^2_{d_j}$ where d_j are the degrees of freedom of the resulting t distribution for $o_{j,t} \cdot \varepsilon_{j,t} \sim t_{d_j}$.

is directly governed by an explicit prior. All that said, our main conclusions below based on the SV-O approach also apply with estimates from the SV-t specification (unreported, using 5 degrees of freedom in the t distribution).

3 Data

Following CCM, our results are based on a VAR including 30 macroeconomic and financial variables, which are listed in Table 1. Reflecting the available samples of the raw data and observations taken by transformations and model lags, the estimation sample is September 1960 to June 2020.[6] Following common practice in the factor model literature as well as studies such as Jurado, Ludvigson, and Ng (2015), after transforming each series for stationarity as needed, we standardize the data (demean and divide by the simple standard deviation) before estimating the model.[7]

Our variable set includes 18 macroeconomic series, chosen for being major indicators within broad categories (production, labor market, etc.). With one exception, we take these series and some financial indicators from the FRED-MD monthly data set detailed in McCracken and Ng (2016), which is similar to that underlying common factor model analyses, such as Stock and Watson (2006). The one exception is the new orders index from the Institute of Supply Management, which FRED-MD is no longer able to include; we instead obtained this series from Haver Analytics.

Our variable set also includes 12 financial series, consisting of the return on the S&P 500, the spread between the Baa bond rate and the 10-year Treasury yield, and a set of additional variables made available by Kenneth French on his web page. Specifically, we use the French series on CRSP excess returns, four risk factors — for SMB (Small Minus Big), HML (High minus Low), R15_R11 (small stock value spread), and momentum — and sector-level returns for a breakdown of five industries (consumer, manufacturing, high technology, health, other).

As discussed in CCM, this specification reflects some choice as to what constitutes a macroeconomic variable rather than a financial variable. Reflecting the typical factor model analysis, the McCracken-Ng data set includes a number of indicators — of stock prices, interest rates, and exchange rates — that may be considered financial indicators. In our model specification, the variables in question are the federal funds rate, the credit spread, and the S&P 500 index. It seems most appropriate to treat the funds rate, as the instrument of monetary policy, as a macro variable. For the other two variables, the distinction between macro and finance is admittedly less

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[6]We took the data from the September release of FRED-MD. Although this vintage has data through June for most series, two of the series in our model only have observations through June (under FRED-MD's usual timing).

[7]To reduce the potential impact of COVID extremes, in the standardization, we computed the means and standard deviations with data through 2019 and omitted 2020 observations.

clear. Whereas Jurado, Ludvigson, and Ng (2015) treat these indicators as macro variables that bear on macroeconomic uncertainty and not directly on financial uncertainty, it seems more natural to consider these indicators as financial variables, in keeping with such precedents as Koop and Korobilis (2014) on the measurement of financial conditions. Accordingly, we include the credit spread and the S&P 500 index in the set of financial variables.

4 Results

This section first provides our estimates of outlier states, time-varying volatilities, and macroeconomic and financial uncertainty. It then presents impulse responses and historical decompositions.

4.1 Volatility and uncertainty estimates

Before taking up the main results of interest, it may be useful to consider the estimation of outlier states in the BVAR-SVF-M-O model. For most financial variables, the posterior mean probabilities of an outlier each month are low, at about 0.5 percent. Mean outlier probabilities are higher for most — although not all — macro variables. For example, the probability estimates are 1.4 percent for employment and 3.9 percent for real personal income.

Figure 1 provides posterior mean estimates of the outlier states $o_{j,t}$ for variable j, covering a subset of variables in the interest of readability. For some variables, reflecting the estimated low probabilities of an outlier, the mean state estimate is flat at 1 for most or much of the sample. At the other extreme, the estimates identify a number of outliers for personal income. More immediate to the matter of the COVID period, a number of variables experience outliers in the period of the COVID disruption to economic activity. For example, the posterior mean of the outlier state (recall that this scales up standard deviations) for consumer spending is 11 in March and 10 in April; the corresponding estimate for employment is 16 in April and 8 in June. As we discuss below, these outlier state movements contribute significantly to the variability of the affected variables of the model. Although a number of variables are found to experience outliers in recent months, it is not a majority of the series; for example, only 8 of the 18 macroeconomic variables in the model have a posterior mean of $o_{j,t}$ of 2 or more in the months of March or April. Accordingly, we proceed with treating the outliers as being independent across variables rather than common to most or all, in keeping with treating common changes in forecast error variances as changes in aggregate uncertainty.[8]

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[8] If we followed conventions in the factor model literature (e.g., McCracken and Ng (2016)) and simply defined an outlier as an observation with distance from the median more than 5 or 10 times the width of the interquartile range,

Turning to overall volatility changes, based on the version of the model including the outlier states, Figure 2 shows the magnitudes of changes in volatilities in recent months, broken into contributions from the uncertainty factors, the outlier states, and the idiosyncratic volatility components.[9] Whereas it would be difficult to compute contributions to changes in the diagonal elements of Σ_t, the variance-covariance matrix of reduced-form innovations in the VAR, it is possible to directly compute percent changes in $\tilde{\lambda}_{j,t}^{0.5} = \sqrt{m_t^{\beta_{j,m}} o_{j,t}^2 h_{j,t}}$ for macro variables and $\tilde{\lambda}_{j,t}^{0.5} = \sqrt{f_t^{\beta_{j,f}} o_{j,t}^2 h_{j,t}}$ for financial variables. For each month t from January 2019 through June 2020, we compute $0.5\ln(\tilde{\lambda}_{j,t}/\tilde{\lambda}_{j,0})$, where $\tilde{\lambda}_{j,0}$ refers to the volatility of December 2018, and the contributions to this percent change in the standard deviation from the uncertainty factors, the outlier states, and the idiosyncratic volatility components. The charts report posterior means of the contributions, as stacked bars.

Perhaps the most immediate result in these estimates is the giant increases in the volatilities of many variables. For example, the log change in $0.5\tilde{\lambda}$ for employment is nearly 5, meaning that volatility (as measured by the standard deviation) has risen by nearly 500 percent. Increases in most of the financial volatilities were more tempered although still dramatic, for example with the return volatilities rising about 100 percent.

In the variance decomposition from the BVAR-SVF-M-O model, the relative importance of uncertainty, outliers, and idiosyncratic volatilities varies across variables. The uncertainty factors drive considerable increases in volatility for all variables. For financial variables, uncertainty factors are the dominant driver. For macro variables, uncertainty factors are important to most increases, but are sometimes dominated by outlier state contributions. As examples, with unemployment and industrial production, the estimates show outliers driving the volatility increases of April (and March for industrial production) and the uncertainty factors driving the increase of May. For some other variables, such as employment, increases in the idiosyncratic volatility components also contribute. But in general, the contributions of the idiosyncratic volatility components are smaller than those of the uncertainty factors and outlier states (and in some cases they lower, rather than raise, volatility).

By comparison, over the period January 2007-December 2009 spanning the Great Recession, Figure 3 shows that the overall rise in volatility was smaller for many variables — although still sizable — with a somewhat different composition than that observed for the COVID period. One

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it would also be the case that only a few macro variables show an outlier in recent months.

[9]In the interest of brevity, we omit corresponding results from the BVAR-SVF-M model without outliers. In these estimates, it is also the case that idiosyncratic contributions are relatively small, and the uncertainty factors almost entirely drive the estimated increases in volatilities.

pattern shared by the Great Recession period is that a sizable increase in aggregate uncertainty helped drive volatility higher. But outliers are estimated to have played a smaller role in 2007-2009 than in 2019-2020, affecting volatilities of only a few variables in the former period but several in the latter. The overall differences in the magnitudes of the volatility changes and the role of outliers point to the COVID period being unique. Another notable difference across the periods is that the idiosyncratic components of the volatility model played a larger role in the earlier recession than in the current one, in several cases (e.g., employment and hours) declining and pulling volatility down but in other cases (e.g., manufacturing and trade sales) rising and boosting volatility.

Turning from variance contributions to the estimates of uncertainty, the top two panels of Figure 4 report the macroeconomic and financial uncertainty estimates, measured as the posterior medians of $m_t^{0.5}$ and $f_t^{0.5}$, respectively. The top panel compares estimates of macroeconomic uncertainty from the BVAR-SVF-M and BVAR-SVF-M-O models, and the second panel makes the same comparison for financial uncertainty. The baseline estimates of the CCM model show dramatic increases in uncertainty, with macroeconomic uncertainty rising from a historical average level of about 1 to a peak of 7.6 in April and edging down to 6.2 in May and 4.9 in June, and with financial uncertainty soaring from an average level of about 1 to a peak of 23.3 in March, before edging down in April and easing some to a level of about 8 in May and June. Although not evident from the long history shown in the chart, the smoothed time series estimates show macroeconomic uncertainty rising significantly starting in the fourth quarter of 2019 and financial uncertainty picking up starting in the third quarter of last year, well in advance of the COVID outbreak.

Estimates of uncertainty from the version of the model with outlier states also show significant increases this year, although less dramatic than those of the CCM baseline and confined to be closer in time to the period of the actual COVID outbreak in the US. More specifically, with the augmented model, the estimate of macroeconomic uncertainty edges up from a historical average level of about 1 in January to 1.2 in February before rising at a faster pace starting in March, peaking at 5.7 in May and moderating to 3.1 in June. The estimate of financial uncertainty picks up significantly over the same months, peaking at 4.1 in March and moderating gradually to 2.8 in June. As a more general matter, looking at the pre-COVID period from 1960 through 2019, adding the outlier states to the CCM has little effect on the time series of macroeconomic uncertainty. The outlier feature has modestly more effect on the historical estimates of financial uncertainty, dampening a little the estimated rise in financial uncertainty around recessions. As to why the treatment of outliers matters a little more for financial uncertainty than for macro uncertainty when outliers

are somewhat more evident for macro variables than financial (see Figure 1), the pattern appears to reflect a combination of factors. In general, the uncertainty estimates are informed by not only conditional variances but also conditional means, and the uncertainty estimates are correlated, so that controlling for outliers that are more prominent in macro variables could affect the estimate of financial uncertainty through conditional mean effects or correlations across uncertainty measures. Moreover, if we modify the model to exclude S&P 500 stock returns and the credit spread, the two financial variables displaying some historical outliers in our reported estimates, then when we compare estimates of the models with and without the outlier states modeled, the estimates of financial uncertainty show less impact of modeling the outliers.

For a given model, there is considerable uncertainty around the estimate of uncertainty in the COVID period. For example, Figure 5 provides the BVAR-SVF-M-O posterior median estimates of macroeconomic ($m_t^{0.5}$) uncertainty along with 70 percent credible sets, for the periods 1960-2019 (top) and January-June 2020 (bottom). Historically, from the start of the sample through December 2019, the width of the credible set averaged 0.2 (compared to an average level of the uncertainty index of 1), with the range commonly rising with spikes in uncertainty, commonly around recessions. Over this period, the width of the credible set peaked at 0.85 in October 2008. As evidenced in the lower panel of Figure 5, the width of the 70 percent credible set has been much greater over the COVID period, peaking at 4.7 in May 2020 (the BVAR-SVF-M yields a much wider credible set around its posterior median estimate of macroeconomic uncertainty). Of course, with additional data as time moves forward and two-sided smoothing, the precision of uncertainty estimates for the first half of 2020 may improve substantially, but by how much remains to be seen.

For comparison to other measures of uncertainty, the bottom panel of Figure 4 provides the VIX measure of uncertainty (through June 2020) and current estimates of macroeconomic and financial uncertainty based on the Jurado, Ludvigson, and Ng (2015) model (through June 2020, posted by Professor Ludvigson). The JLN estimates show a significant rise, with macroeconomic uncertainty increasing 39 percent from December 2019 to a peak in March 2020 and financial uncertainty increasing 32 percent over the same period. These increases are of course much more modest than those evident from our models. However, that is in keeping with historical patterns, in which our uncertainty estimates rise more than those of JLN around recessions (of course, this need not mean that our uncertainty measures yield larger impacts on the economy, since the greater sensitivity of the uncertainty measure to the cycle will get reflected in smaller response coefficients). The greater variability of our measures could stem from the various differences in our modeling approach as

compared to JLN, including the fact that, in our one-step approach to estimating uncertainty and its effects on the economy, uncertainty responds directly to fluctuations in the economy, through the inclusion of y_{t-1} in the time series process of the factors.[10] The VIX measure of uncertainty displays a sharper rise, with the VIX more than tripling from January to March before drifting down over the following few months. As of July, this measure remains at an elevated level but not outside of the norms of previous recessions. Caggiano, Castelnuovo, and Kima (2020) use estimates of a small VAR through April 2019 and scale up the size of a shock to the VIX to gauge (via impulse responses) the effects of the rise in uncertainty on world output during the pandemic, concluding that the effects are sizable. Altig, et al. (2020) review and compare movements of a range of measures of uncertainty before and during the pandemic.

4.2 Impulse responses

To provide a basic assessment of the effects of macroeconomic and financial uncertainty, for both the baseline CCM model and our outliers-robust extension, we compute impulse response functions for each of the 5000 retained draws of the VAR's parameters and latent states and report the posterior medians and 70 percent credible sets of these functions. To save space, for a given shock of the size of one standard deviation, we report response estimates for both models, using (i) black lines and gray shaded regions for posterior medians and 70 percent credible sets from the BVAR-SVF-M-O specification and (ii) red and blue lines for posterior medians and 70 percent credible sets from the BVAR-SVF-M specification. For similar reasons, the charts below provide results for a subset of selected variables. Note that, although the models are estimated with standardized data, for comparability to previous studies the impulse responses are scaled and transformed back to the units typical in the literature. We do so by using the model estimates to: (1) obtain impulse responses in standardized, sometimes (i.e., for some variables) differenced data; (2) multiply the impulse responses for each variable by the standard deviations used in standardizing the data before model estimation; and (3) accumulate the impulse responses of step (2) as appropriate to get back impulse responses in levels or log levels. Accordingly, the units of the reported impulse responses are percentage point changes (based on 100 times the log levels for variables in logs or rates for variables not in log terms).

In broad terms, the impulse response estimates from the two models reported in Figures 6 (macroeconomic uncertainty) and 7 (financial uncertainty) are comparable and qualitatively the

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[10]In contrast, the JLN measures of uncertainty are obtained as simple averages of conventional stochastic volatility estimates obtained from simple autoregressive models (augmented to include factor indexes of the economy) of each series, without direct feedback of economic conditions to volatility.

same as those discussed in detail in CCM.[11] As shown in the penultimate panel of Figure 6, the shock to log macro uncertainty produces a rise in uncertainty that gradually dies out. Economic activity and the labor market decline in response, with indicators such as consumer spending, housing starts and permits, manufacturing and trade sales, the ISM index of new orders, employment, and hours worked falling. Despite the significant decline of economic activity in response to the macro uncertainty shock, there doesn't appear to be evidence of a broad decline in prices. The PPI for finished goods declines steadily, but the response is estimated imprecisely. Consumer prices as captured by the PCE price index instead rise but also fail to display a significant change. Overall, as noted in CCM, this picture of price responses is in line with New Keynesian models, which predict a small effect of uncertainty on inflation due to sticky prices (and possibly wages). In the face of this sizable deterioration in the real economy and in the absence of much movement in prices, the federal funds rate gradually falls.[12] The responses of financial indicators to the shock to macro uncertainty are — collectively speaking — muted and imprecisely estimated. One exception is the spread between the Baa and 10-year Treasury yields, which displays a modest, but persistent and significant, rise, with a hump-shaped pattern. Aggregate stock prices and returns, as captured by the S&P 500 price index and the CRSP excess returns, decline but fail to display significant changes.

Similarly, the estimates of responses to a financial uncertainty shock in Figure 7 are broadly similar across models and similar to the estimates of CCM. As reported in the last panel, the shock to log financial uncertainty produces a rise in uncertainty that gradually dies out. The financial uncertainty shock affects economic activity much as does a shock to macroeconomic uncertainty. In particular, the financial uncertainty shock depresses economic activity and leads to reductions in the federal funds rate and a rise (and eventual decline) in the credit spread. The most notable difference with respect to results for a macro uncertainty shock is that a financial uncertainty shock leads to a sizable falloff in aggregate stock prices and returns. The response of the S&P500 price level is negative and significant. The CRSP excess returns display a negative jump and then gradually recover. However, the responses of the risk factors included in the model are insignificant.

Focusing on a comparison of the BVAR-SVF-M and BVAR-SVF-M-O estimates, the most

[11]One difference in these results as compared to those in CCM is that, in these estimates, a shock to macro uncertainty does not yield a significant rise in financial uncertainty, whereas a shock to financial uncertainty produces a significant rise in macro uncertainty; the pattern was reversed in the CCM estimates. This appears to reflect the information in the data since the end of the CCM sample in mid-2014. In general, macro and financial uncertainty are significantly correlated, and causal responses of one to the other can be difficult to disentangle.

[12]Estimates of uncertainty and impulse responses obtained with the shadow rate of Wu and Xia (2016) replacing the funds rate are very similar.

noticeable difference is that, particularly in the case of a macro uncertainty shock, credible sets are typically wider for the BVAR-SVF-M estimates than for the BVAR-SVF-M-O estimates (although not shown, the BVAR-SVF-M sets are also typically wider than the original impulse response estimates of CCM). For example, in the case of the employment response to a macro uncertainty shock, at the 24-month horizon, the 70 percent credible set has a width of 0.36 percentage point with the BVAR-SVF-M model and 0.24 percentage point with the BVAR-SVF-M-O model. These wider bands for economic variables reflect a wider band around the response of macro uncertainty to its shock in the BVAR-SVF-M estimates as compared to the outliers-robust estimates. In any event, posterior medians are similar across the models, although estimated magnitudes of responses to the macro shock seem to be a little smaller with the BVAR-SVF-M-O model than with the BVAR-SVF-M model (which looks to be due to the fact that the uncertainty shock dissipates a little faster with the former than with the latter).

4.3 Historical decompositions

To assess the specific role of fluctuations in uncertainty shocks in the economy and financial markets in the period of the COVID-19 pandemic, we estimate historical decompositions. In a standard linear model, a historical decomposition of the total s-steps-ahead prediction error variance of y_{t+s} can be easily obtained by constructing a baseline path (forecast) without shocks, and then constructing the contribution of shocks. With linearity, the sums of the shock contributions and the baseline path equal the data. In our case, the usual decomposition cannot be directly applied because of interactions between Λ_{t+s} and ϵ_{t+s}: Shocks to log uncertainty affect the forecast errors through $\Lambda_{t+s}\epsilon_{t+s}$, and, over time, shocks ϵ_{t+s} affect Λ_{t+s} through the response of uncertainty to lagged y. CCM used a decomposition of the total contribution of the shocks into three parts: (i) the direct contributions of the uncertainty shocks u_{t+s} to the evolution of y; (ii) the direct contributions of the VAR "structural" shocks ϵ_{t+s} to the path of y taking account of movements in Σ_{t+s} that arise as uncertainty responds to y but abstracting from movements in Σ_{t+s} due to uncertainty shocks; and (iii) the interaction between shocks to uncertainty and the structural shocks ϵ_{t+s}.

To be more specific, consider a simple one-factor model with lag orders of 1, abstracting from outlier states:

$$\begin{cases} y_t = \Pi y_{t-1} + \Gamma_1 m_t + \Gamma_2 m_{t-1} + v_t \\ \quad m_t = \delta y_{t-1} + \gamma m_{t-1} + u_t \end{cases}, \tag{6}$$

where v_t and u_t are independent, with variances Σ_t and Φ_u, respectively. So we can replace v_t above with $\Sigma_t^{0.5}\epsilon_t$, where $\Sigma_t^{0.5}$ is a shortcut notation for the Cholesky decomposition of Σ_t and ϵ_t is $N(0, I_n)$. The one-step-ahead forecast errors are $y_{t+1} - E_t y_{t+1} = \Sigma_{t+1}^{0.5}\epsilon_{t+1} + \Gamma_1 u_{t+1}$. Now let

14

$\hat{\Sigma}_{t+s|t}$ denote the future error variance matrix that would prevail in the absence of future shocks to uncertainty. This would be constructed from forecasts of future uncertainty accounting for movements in y driven by ϵ shocks and the path of idiosyncratic volatility terms (incorporating shocks to these terms). The following decomposition can be obtained by adding and subtracting $\hat{\Sigma}_{t+1|t}$ terms in the forecast error:

$$y_{t+1} - E_t y_{t+1} = \Gamma_1 u_{t+1} + \hat{\Sigma}_{t+1|t}^{0.5} \epsilon_{t+1} + (\Sigma_{t+1}^{0.5} - \hat{\Sigma}_{t+1|t}^{0.5}) \epsilon_{t+1}. \tag{7}$$

In this decomposition, the first term gives the direct contribution of the uncertainty shock, the second term gives the direct contribution of the structural shocks to the VAR, and the third term gives the interaction component. The third term can be simply measured as a residual contribution, as the data less the direct contributions from the uncertainty shock and the structural shocks to the VAR.

One complication with this approach is that, in the interaction components, there is not a good way to separate the roles of aggregate uncertainty and idiosyncratic volatility, because Σ_t is the product of such terms containing innovations to aggregate uncertainty and innovations to idiosyncratic components. Since the terms are multiplicative and not additive, there isn't a clear way to isolate the role of aggregate uncertainty from the role of idiosyncratic components. In light of these complications, and because the interaction effects are empirically much less pronounced than the direct effects, CCM did not attempt to separate the roles of aggregate uncertainty and idiosyncratic volatility in the interaction component. CCM's reported results focused on the more important contributions from the first two pieces of the decomposition, shocks to uncertainty and VAR shocks.

In the recent extreme variation in the data, the interaction term of the simple decomposition drives much of the variation in some variables. Such a pattern of course means that the variation is difficult to decompose in a meaningfully complete way. However, in this paper, we are primarily interested in the magnitudes of the contributions of uncertainty shocks. As a result, we simplify the historical decomposition analysis and focus on just contributions from uncertainty shocks. In the simple one-step-ahead example, the direct contribution from uncertainty shocks is measured by just $\Gamma_1 u_{t+1}$; this contribution and contributions at later periods are easily computed.

Figures 8 and 9 provide the estimated contributions from uncertainty shocks (stacked bars), along with the actual data (black lines), for January 2019 through June 2020. The charts show the data series (demeaned for simplicity) and the direct contributions of shocks to (separately) macroeconomic and financial uncertainty. Note that these charts use two scales, with the left for

15

the data and the right for the contributions of the uncertainty shocks. The reported estimates are posterior medians of decompositions computed for each draw from the posterior. In light of space constraints, the charts provide results for a subset of selected variables.

In the BVAR-SVF-M model's historical decomposition for 2019-2020, uncertainty shocks account for some of the sharp data changes that have occurred in recent months. By historical standards, the contributions are sizable; in fact, for many of the variables, the contributions of uncertainty shocks are larger in 2020 than during the Great Recession (using results for a 2003-2014 decomposition not reported in the interest of brevity). But in the COVID period, the contributions of uncertainty shocks are dwarfed by the dramatic size of the total changes. For example, averaged in the months of March and April (the worst months of the pandemic), combined shocks to macroeconomic and financial uncertainty pulled down employment and consumption by about 15 basis points and industrial production by 60 basis points. Annualized (multiplied by 12), these are large contributions. But averaged over March and April, the actual growth rates of employment, consumption, and industrial production (with historical mean growth rates removed) fell by unprecedented magnitudes of 8, 10, and 9 percent, respectively. Consistent with the impulse response estimates, shocks to macroeconomic uncertainty are more important to macro variables than are shocks to financial uncertainty, and the reverse applies for financial variables.

Estimates of the historical decomposition from the BVAR-SVF-M-O model are qualitatively very similar to those from the BVAR-SVF-M specification of CCM. The main change is that, with outliers modeled, the estimated contributions of uncertainty shocks are slightly or modestly reduced compared to the BVAR-SVF-M estimates. For example, averaged in the months of March and April, combined shocks to macroeconomic and financial uncertainty pulled down employment by about 10 basis points, consumption by 15 basis points, and industrial production by 50 basis points. In general, the smaller rise in uncertainty that occurs with the outliers-robust version of the model would be expected to reduce contributions of uncertainty to this year's fluctuations in economic and financial indicators, and the historical decomposition bears that out, with slight to modest effects.

As sizable as our estimates of the contributions of uncertainty to the COVID downturn are by historical standards, some research has obtained even larger estimates. Pellegrino, Castelnuovo, and Caggiano (2020) and Pellegrino, Ravenna, and Zullig (2020) obtain larger effects of an uncertainty shock using a nonlinear VAR in which uncertainty shocks can have more adverse effects during recessions than during normal times. In addition, Barrero and Bloom (2020) suggest that

uncertainty will reduce US GDP growth in 2020 by 2 to 3 percent (on a four-quarter basis); with data for the first half of the year in hand, private-sector forecasters surveyed by the *Wall Street Journal* in mid-September put GDP growth for the year at about -4 percent. These estimated effects of uncertainty are based on the cross-country methodology of Baker, Bloom, and Terry (2020), who relate GDP growth to uncertainty as measured by stock market volatility and who address possible endogeneity by instrumenting with episodes of natural disasters, terrorist attacks, and political shocks. The difference in magnitudes in their results as compared to ours likely is at least in part due to methodology and probably less due to the measure of uncertainty. We say this based on a simple comparison to BVAR estimates (methodology like ours) that measure uncertainty with stock market volatility (underlying uncertainty measure relied on by Barrero and Bloom). In unreported results, if we use stock market volatility as the measure of uncertainty and add it to a conventional BVAR with uncertainty ordered first, the peak effect of the contributions to shocks to uncertainty is about -2 percentage points for employment, consumption, and industrial production — sizable but still well short of the peak 15 percent decline seen in the actual data. We conjecture that their cross-country instrumental variables approach based on historical disasters boosts the estimated effects.[13] Ludvigson, Ma, and Ng (2020) use structural VARs and historical data on natural disasters to estimate COVID's effects on the economy and uncertainty. In their estimates, treating COVID as a disaster-type shock (and calibrating its immense size) yields declines in activity indicators like those observed in the data, as well as a rise in economic and financial uncertainty due to the disaster shock.

In the broader context of uncertainty and its effects, particularly in a period as unusual as that of the pandemic, we should emphasize that our estimates obtained by Bayesian methods are explicitly conditional on the model and the data available to date. Over time, as more data become available, the model's estimates of uncertainty and contributions to the economic fluctuations of the COVID period could change. Moreover, there are some respects in which uncertainty could matter in ways outside the scope of our aggregate model. In particular, uncertainty at a micro level could have important effects, particularly in the COVID downturn. Some of the uncertainty literature (pre-COVID) has emphasized the important role of volatility shifts at the micro level (see, e.g., Bloom, et al. (2018)). Such micro changes need not be captured as aggregate uncertainty in models such as ours. The subjective uncertainty indicators considered in Altig, et al. (2020) display a sizable rise in firm-level uncertainty following the COVID outbreak. In addition, Knightian uncertainty may

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[13]Consistent with this, Baker, Bloom, and Terry (2020) obtain smaller estimated effects with a different VAR-based identification applied to just US data.

have been particularly important in the months immediately following the pandemic's outbreak, as some kinds of economic activity shut down in unprecedented ways.

5   Conclusions

In this paper we measure the effects of the COVID-19 outbreak on macroeconomic and financial uncertainty, and the consequences of the latter for key economic variables.

We use a large, heteroskedastic vector autoregression (VAR) in which the error volatilities share two common factors, interpreted as macro and financial uncertainty, in addition to idiosyncratic components. Macro and financial uncertainty are allowed to contemporaneously affect the macroeconomy and financial conditions, with changes in the common component of the volatilities providing contemporaneous identifying information on uncertainty.

We also consider an extended version of the model, based on a latent state approach to accommodating outliers in volatility, to reduce the influence of extreme observations from the COVID period.

The estimates we obtain yield very large increases in macroeconomic and financial uncertainty over the course of the COVID-19 period. These increases have contributed to the downturn in economic and financial conditions, but with both models, the contributions of uncertainty are small compared to the overall movements in many macroeconomic and financial indicators. That implies that the downturn is driven more by COVID-related supply and demand shocks that, at least with our methodology, are not measured as shocks to aggregate uncertainty. Although our two models yield qualitatively very similar results, their estimates differ along some clear dimensions. Including the outlier treatment in the model mitigates the measured rise in macroeconomic and financial uncertainty and modestly reduces the estimated contributions to recent fluctuations in economic and financial indicators. Although both sets of estimates are plausible in our judgment, we are inclined to favor the measures from the outliers-robust model for yielding estimates that better capture the timing of the pandemic's outbreak.

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Table 1: Variables in the baseline model

Macroeconomic variables	Financial variables
All employees: total nonfarm ($\Delta \ln$)	S&P 500 ($\Delta \ln$)
Industrial production index ($\Delta \ln$)	Spread, Baa-10y Treasury
Capacity utilization: manufacturing (Δ)	Excess return
Help wanted to unemployed ratio (Δ)	SMB FF factor
Unemployment rate (Δ)	HML FF factor
Real personal income ($\Delta \ln$)	Momentum factor
Weekly hours: goods-producing	R15_R11
Housing starts ($\ln$)	Industry 1 return
Housing permits ($\ln$)	Industry 2 return
Real consumer spending ($\Delta \ln$)	Industry 3 return
Real manuf. and trade sales ($\Delta \ln$)	Industry 4 return
ISM: new orders index	Industry 5 return
Orders for durable goods ($\Delta \ln$)	
Avg. hourly earnings, goods-producing ($\Delta^2 \ln$)	
PPI, finished goods ($\Delta^2 \ln$)	
PPI, commodities (primary metals, $\Delta^2 \ln$)	
PCE price index ($\Delta^2 \ln$)	
Federal funds rate (Δ)	

Note: For those variables transformed for use in the model, the table indicates the transformation in parentheses following the variable description.
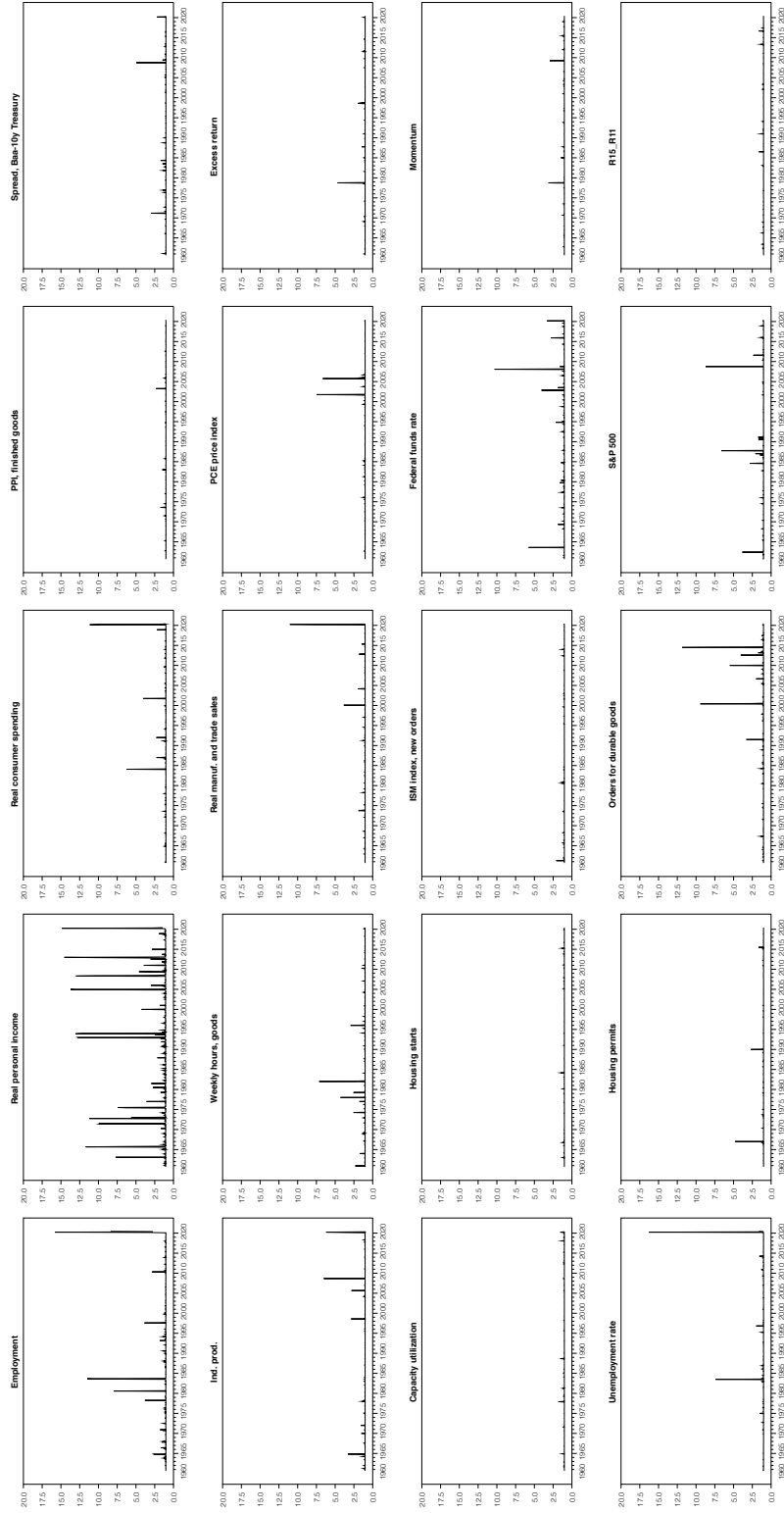
Figure 1: Posterior means of outlier states, BVAR-SVF-M-O
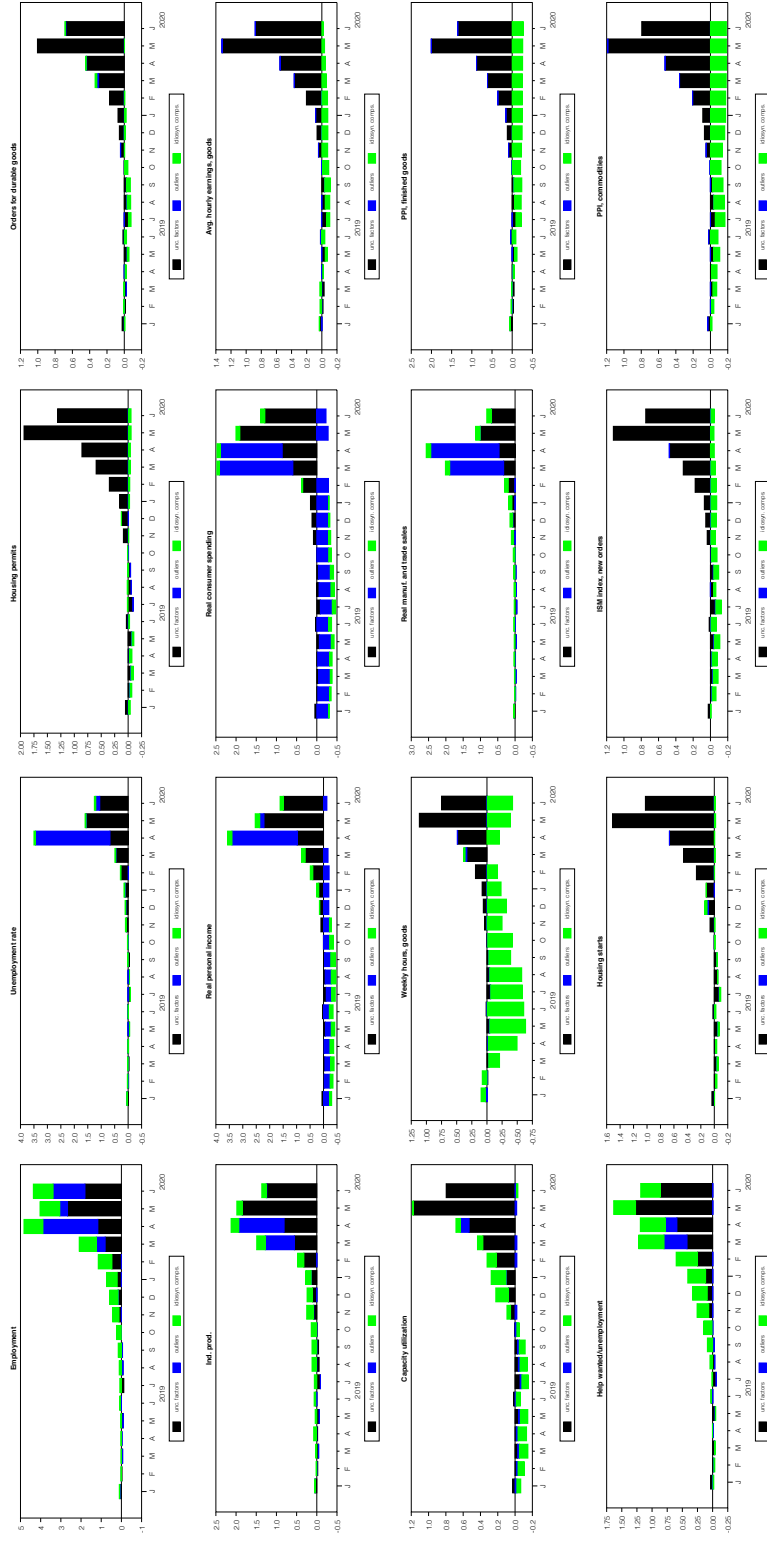
Figure 2: Posterior means of contributions to percent changes in volatilities, measured as $\Delta \ln \tilde{\lambda}_{i,t}^{0.5}$, BVAR-SVF-M-O
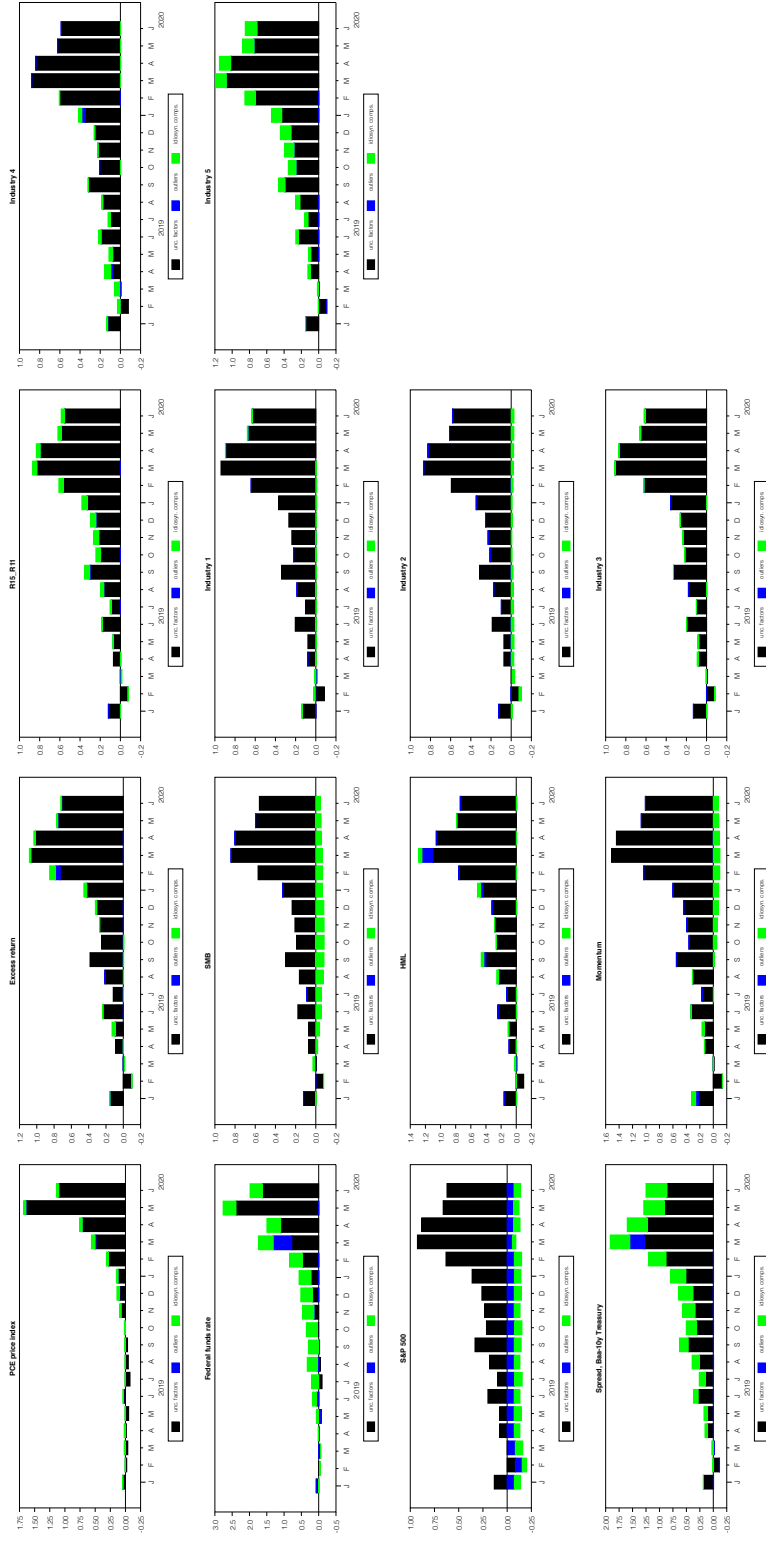
Figure 2: Continued, means of contributions to percent changes in volatilities, measured as $\Delta \ln \tilde{\lambda}_{i,t}^{0.5}$, BVAR-SVF-M-O
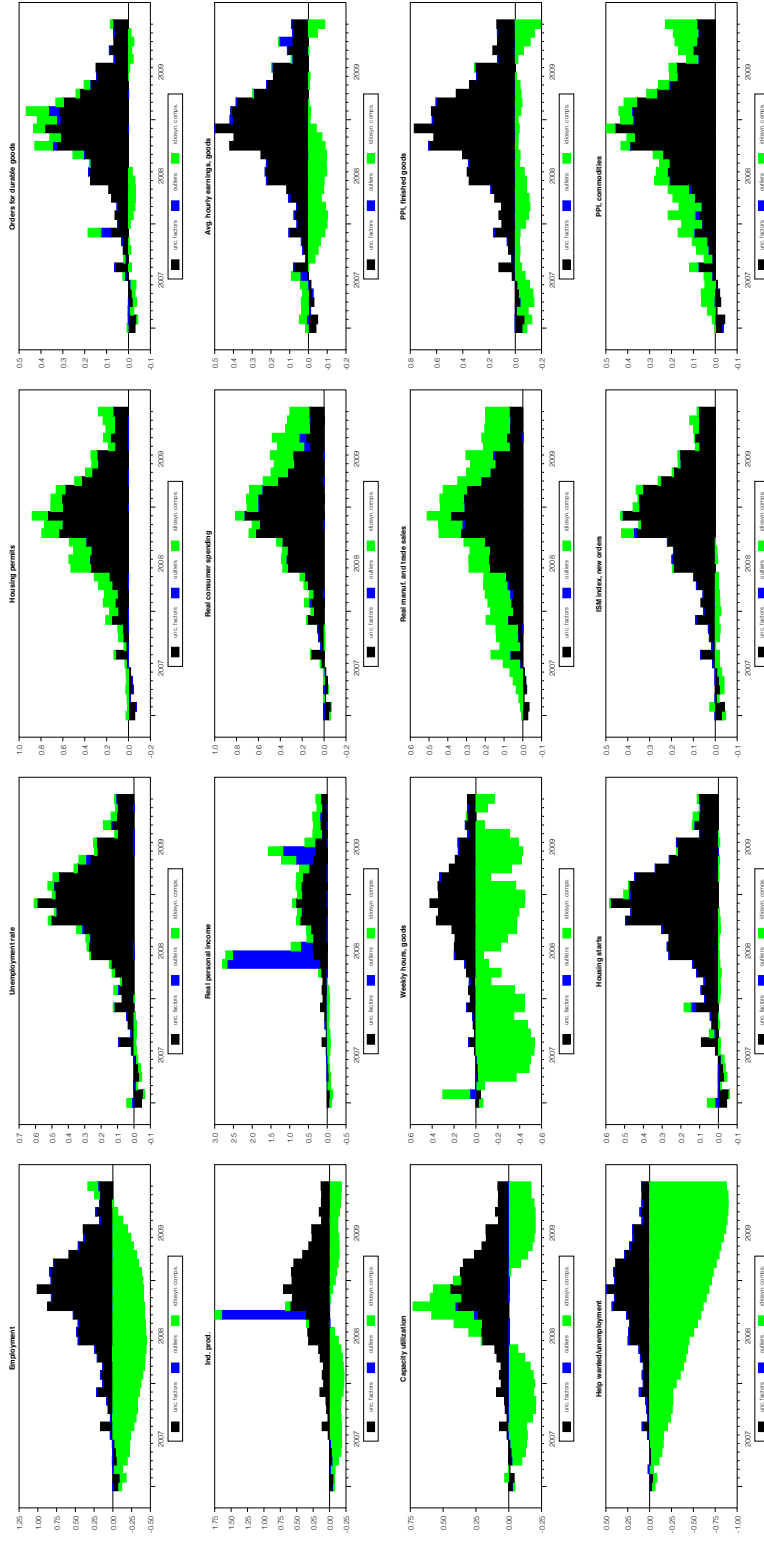
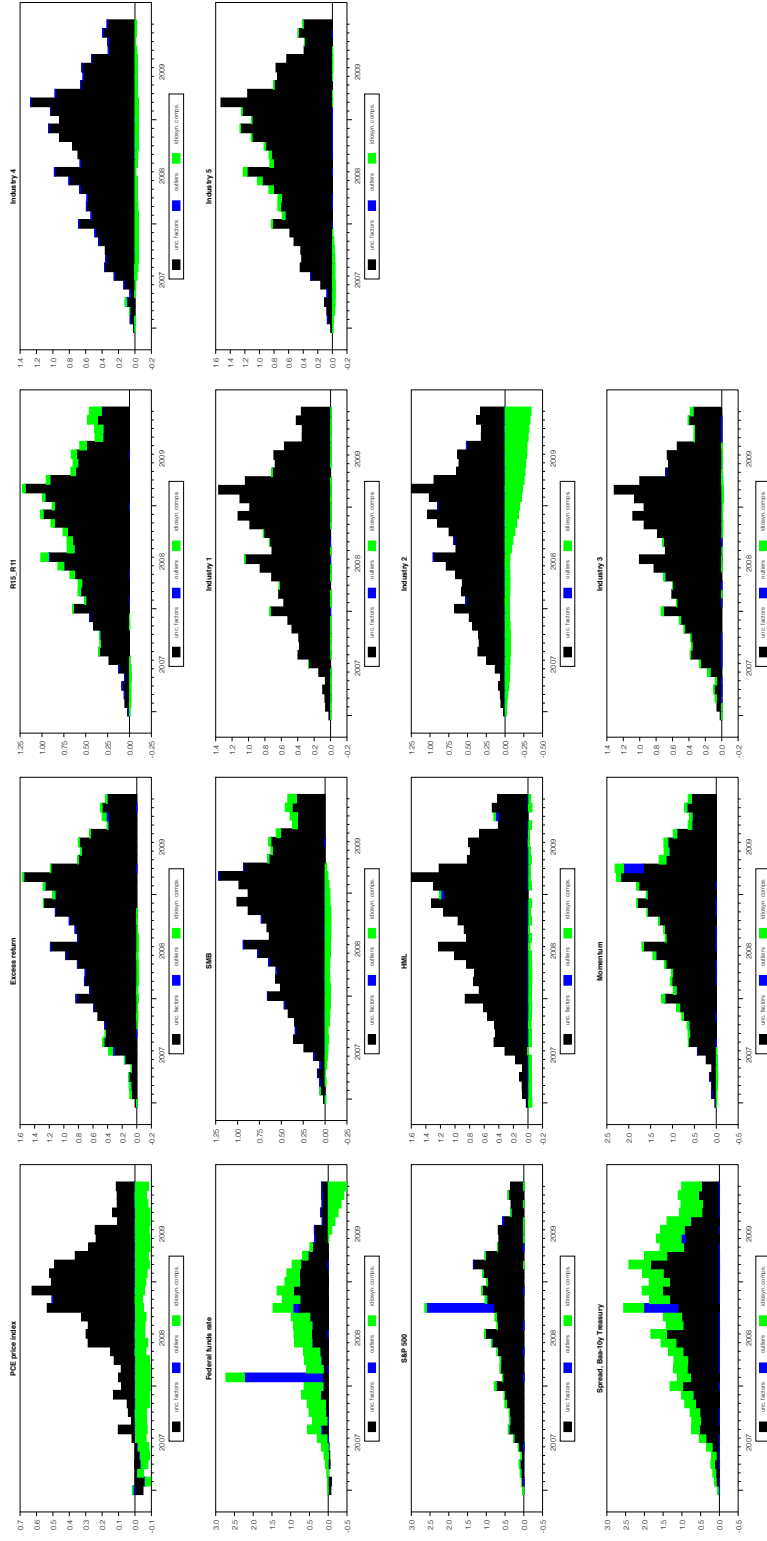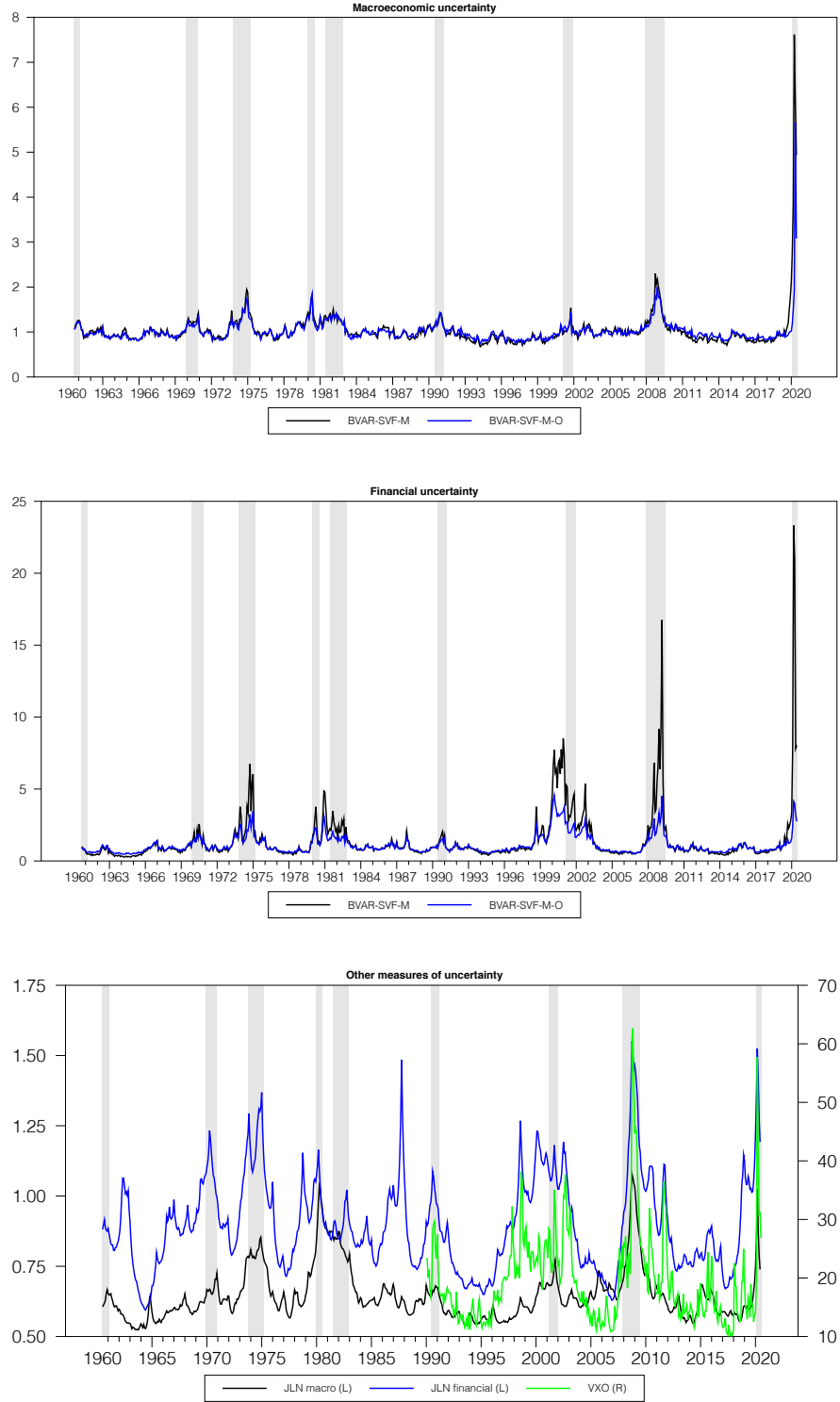Figure 3: Posterior means of contributions to percent changes in volatilities in the Great Recession, measured as $\Delta \ln \tilde{\lambda}_{i,t}^{0.5}$, BVAR-SVF-M-O

25

Figure 3: Continued, means of contributions to percent changes in volatilities in the Great Recession, measured as $\Delta \ln \tilde{\lambda}_{i,t}^{0.5}$, BVAR-SVF-M-O

Figure 4: The top two panels report posterior median estimates of the macroeconomic ($m_t^{0.5}$, top) and financial uncertainty ($f_t^{0.5}$, middle) factors from the BVAR-SVF-M and BVAR-SVF-M-O models. The bottom panel provides the uncertainty estimates of Jurado, Ludvigson, and Ng (2015) and the VIX measure of uncertainty. Shaded regions denote periods between NBER business cycle peaks and troughs.

27
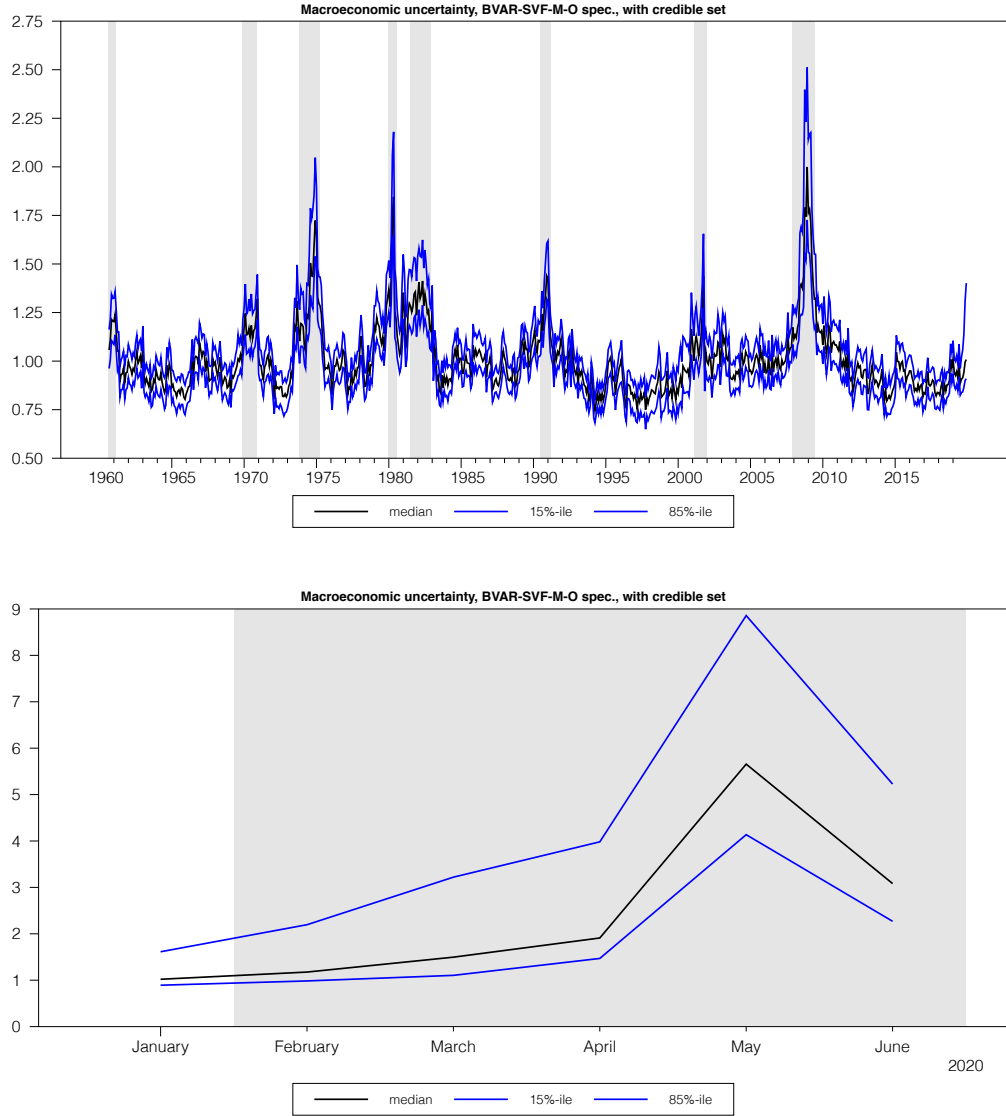
Figure 5: The panels report BVAR-SVF-M-O posterior median estimates of macroeconomic ($m_t^{0.5}$) uncertainty along with 70 percent credible sets, for the periods 1960-2019 (top) and January-June 2020 (bottom). Shaded regions denote periods between NBER business cycle peaks and troughs.
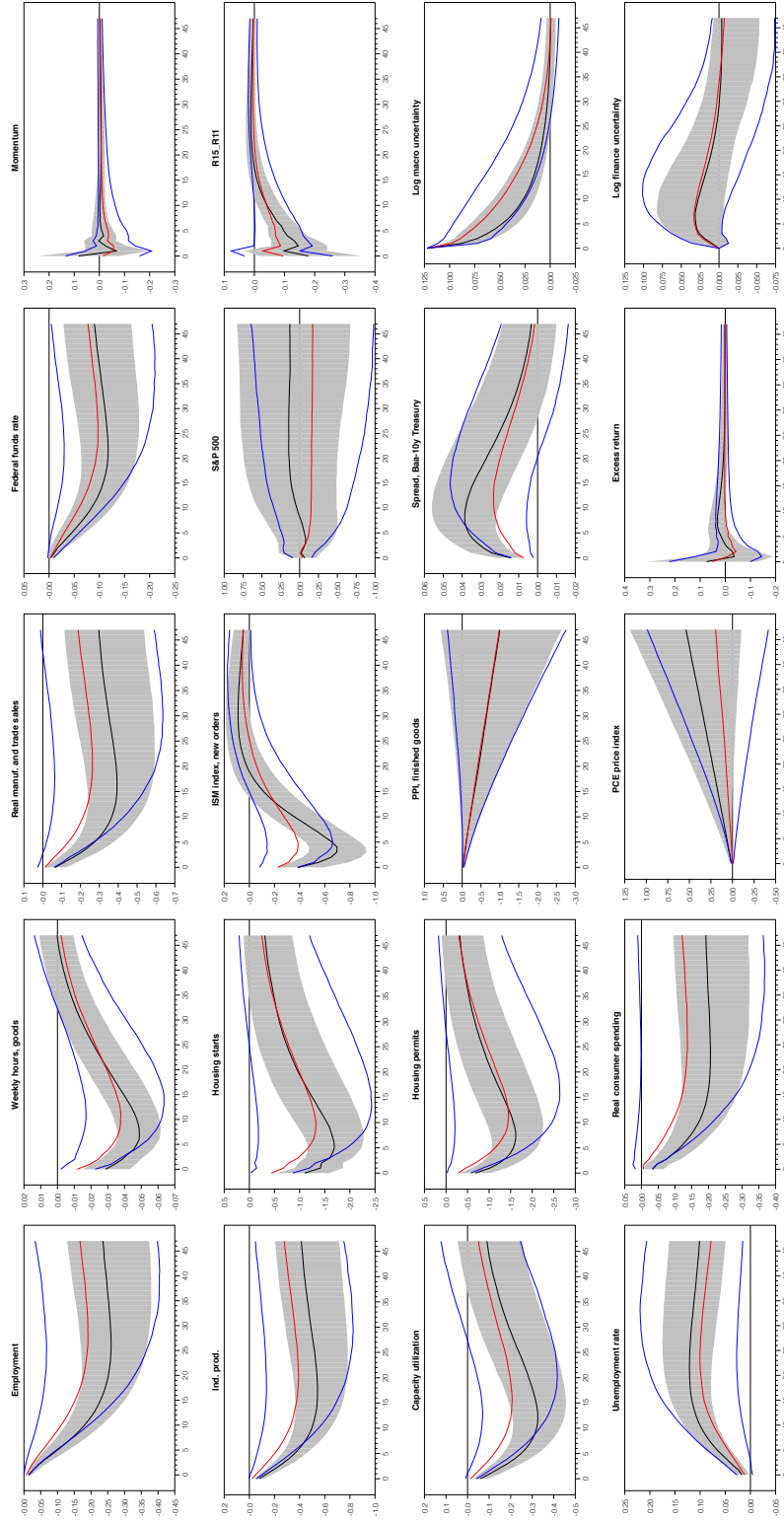
Figure 6: Impulse response estimates for shock to macroeconomic uncertainty. The black line and gray shaded region provide posterior medians and 70 percent credible sets from the BVAR-SVF-M-O specification. The red and blue lines provide posterior medians and 70 percent credible sets from the BVAR-SVF-M specification.
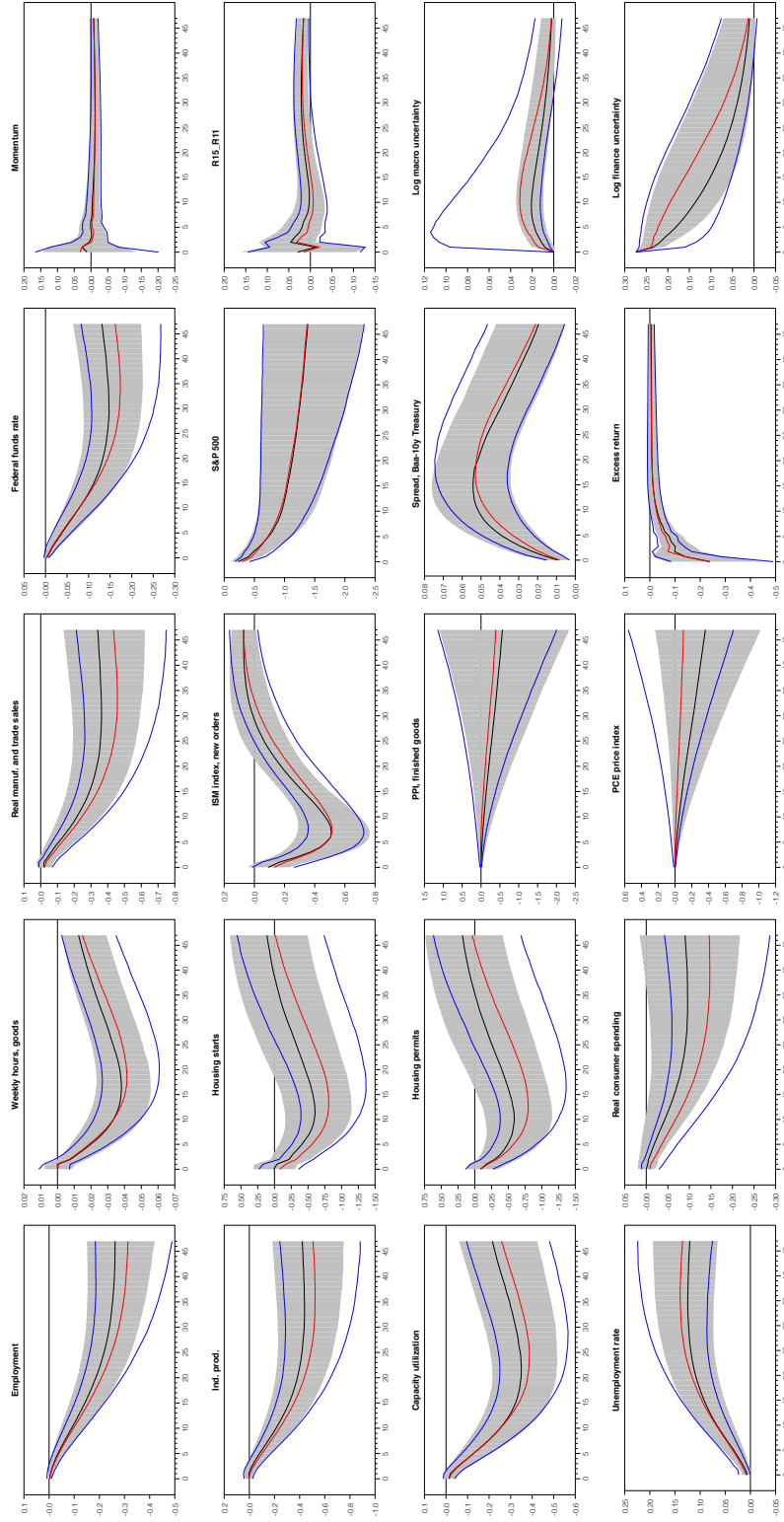
Figure 7: Impulse response estimates for shock to financial uncertainty. The black line and gray shaded region provide posterior medians and 70 percent credible sets from the BVAR-SVF-M-O specification. The red and blue lines provide posterior medians and 70 percent credible sets from the BVAR-SVF-M specification.
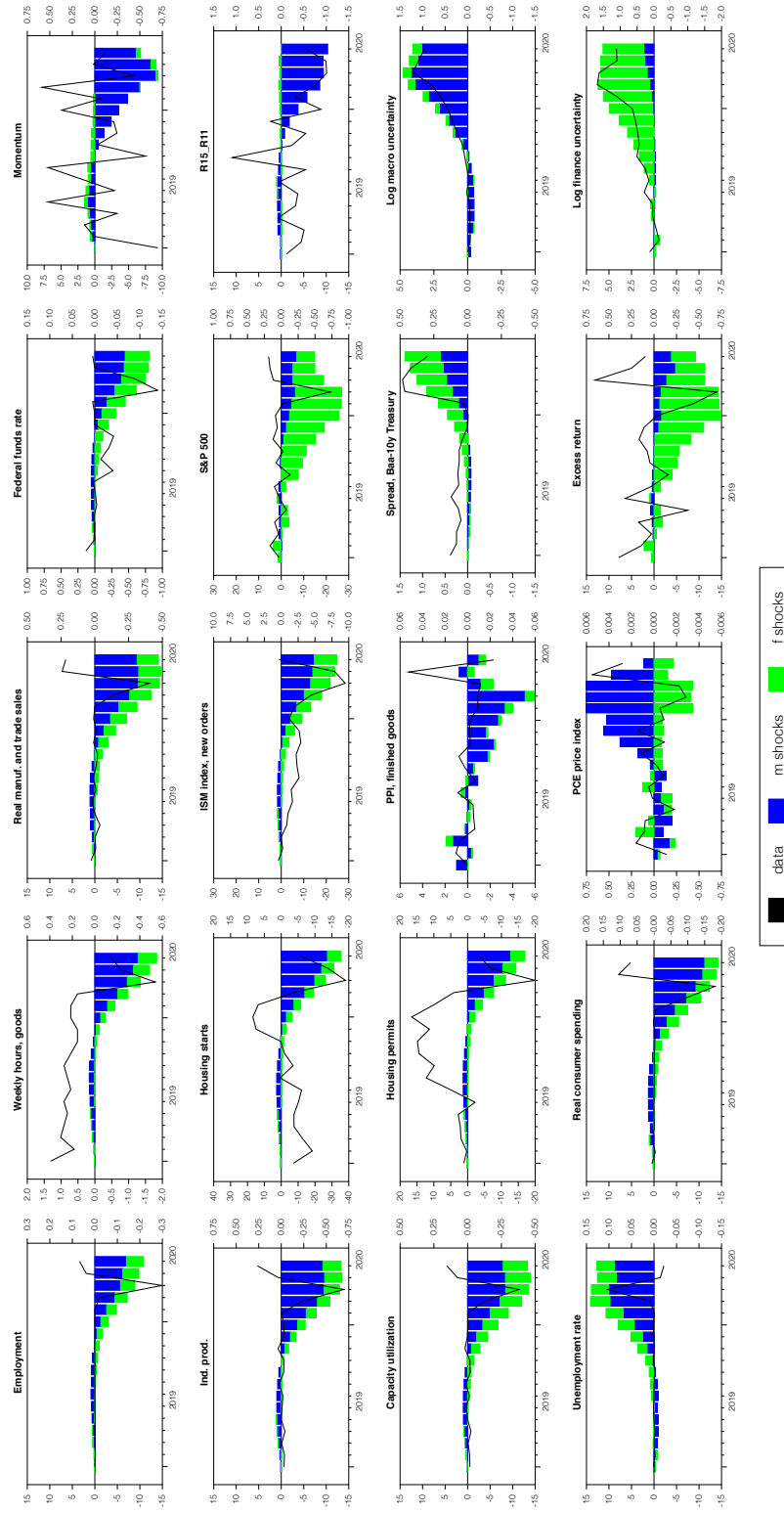
Figure 8: Historical decomposition (posterior medians) with contributions from just uncertainty shocks, January 2019-May 2020, BVAR-SVF-M. Chart is two-scale, with scale for actual data on the left side and scale for estimation contributions on the right.
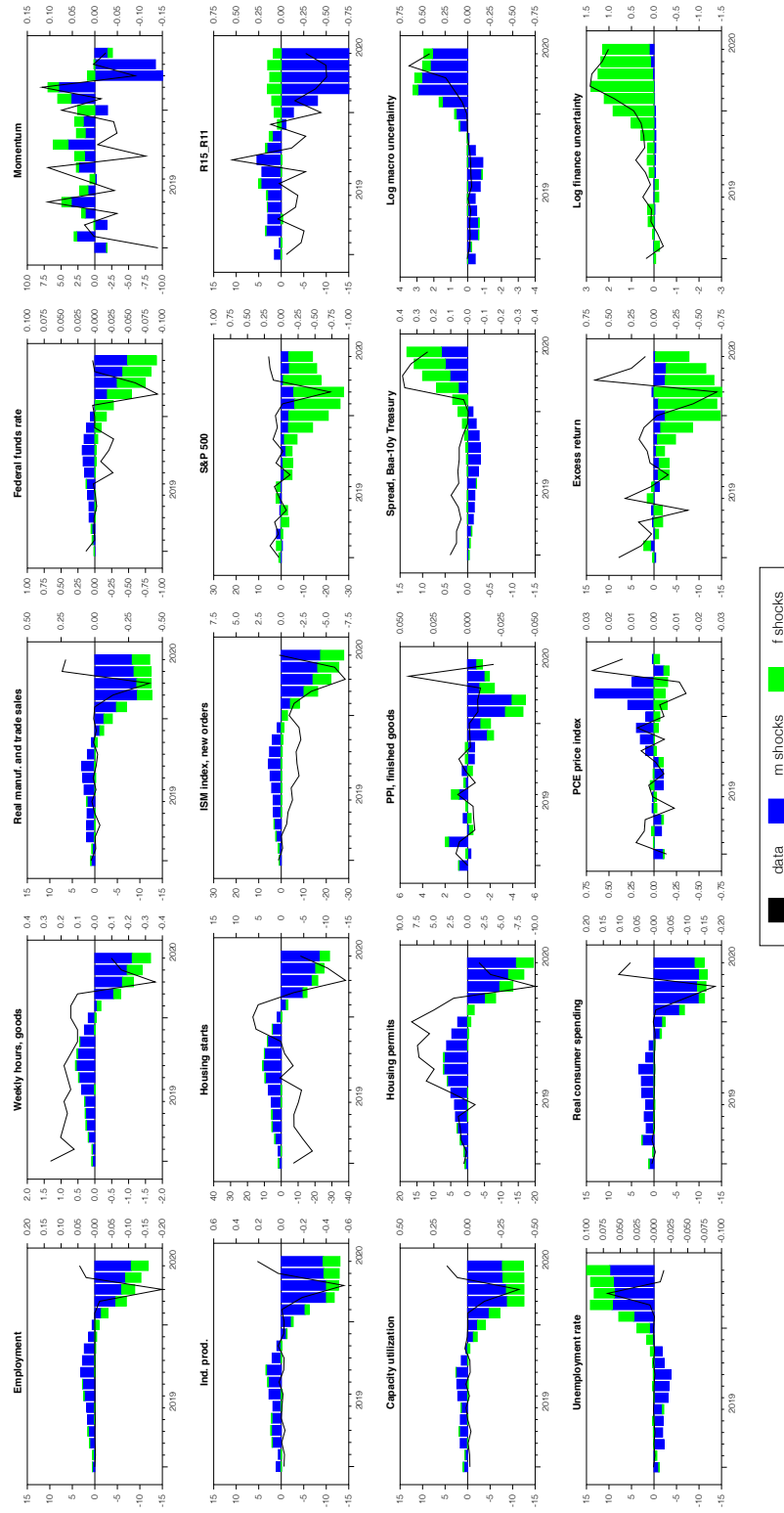
Figure 9: Historical decomposition (posterior medians) with contributions from just uncertainty shocks, January 2019-May 2020, BVAR-SVF-M-O. Chart is two-scale, with scale for actual data on the left side and scale for estimation contributions on the right.