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Sequencing the COVID-19 Recession in the USA: What Were the Macroeconomic Drivers?

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Abstract

We apply a structural vectorautoregressive analysis to decompose fluctuations in the growth rate of industrial production and inflation precipitated by the COVID-19 pandemic in the USA into aggregate demand, aggregate supply, and uncertainty shocks. While all three types of shocks contributed to output and inflation dynamics, the surge in economic uncertainty contributed to the decline in output more strongly than aggregate demand or aggregate supply disruptions. In 2021, the decline in uncertainty and adverse aggregate supply shocks emerged to be similarly important in spurring inflation.

I. Introduction

The COVID-19 pandemic caused a particularly severe, swift, and globally synchronized recession. Widespread lockdowns and disruptions in supply chains gave rise to adverse aggregate supply effects (Bonadio *et al.*, 2021). At the same time, lockdowns resulted in income shortfalls and limited consumption opportunities, dampening aggregate demand (Eichenbaum, Rebelo, and Trabandt, 2021; Kapetanios *et al.*, 2022). Moreover, due to its unprecedented nature, the pandemic increased uncertainty, which potentially induced consumers and firms to postpone spending and investment (Altig *et al.*, 2020). Thus, output and inflation dynamics are likely to be the result of a combination of shocks that contributed simultaneously during the pandemic.

In this paper, we study the macroeconomic implications of the COVID-19 pandemic for the US economy by decomposing output growth and inflation dynamics into contributions of standard macroeconomic shocks. This approach allows us to quantify and compare the relative contributions of the individual shocks. In addition, we contribute to the existing literature by studying how the relative importance of the different shocks evolved over time as different forces may have been at play during the pandemic-induced

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recession and the subsequent recovery.[1] From a policy perspective, identifying the main drivers of output and inflation dynamics and characterising their potentially time-varying contributions is relevant since the effects of policy measures depend on the type of shock that hits the economy. For instance, policies that support aggregate demand are presumably less effective if the economy primarily faces adverse supply-side developments.

Our analysis is based on structural vectorautoregressive (VAR) models. To identify orthogonal structural shocks, we rely on sign restrictions on impulse response functions (Faust, 1998; Canova and Nicoló, 2002; Uhlig, 2005), and narrative sign restrictions (Antolín-Díaz and Rubio-Ramírez, 2018; Ludvigson, Ma, and Ng, 2021) that exploit information about the timing and the magnitude of structural shocks. The combination of these two identification approaches allows us to disentangle the shocks that we are interested in and to narrow down the set of admissible models.[2] Specifically, we identify aggregate supply and aggregate demand shocks by imposing discriminating sign restrictions on the response of the inflation rate, as is standard (see e.g. Fry and Pagan, 2011; Furlanetto, Ravazzolo, and Sarferaz, 2017; Calvert Jump and Kohler, 2022), and impose additional narrative restrictions, which are based on Ludvigson *et al.* (2021), to identify uncertainty shocks. Since we impose the narrative restrictions only in months well before the pandemic, we leave the realisations and the effects of uncertainty shocks unrestricted during the pandemic itself.

We find that the dynamics of industrial production growth during the COVID-19 pandemic were dominated by adverse uncertainty shocks. While aggregate supply and aggregate demand shocks contributed to the decline in industrial production growth as well, uncertainty shocks exerted by far the largest effects. The negative contributions of aggregate demand shocks faded soon after the initial downturn, while aggregate supply shocks slowed down economic activity more persistently. The most pronounced contribution to the acceleration of industrial production growth during the subsequent recovery can be attributed to a decline in uncertainty.

For inflation dynamics, we find that aggregate demand and especially uncertainty shocks contributed to the downward pressure on inflation during the downturn. Aggregate supply shocks counteracted the decline in inflation during the early phase and, together with expansionary uncertainty shocks, contributed to inflationary pressure towards the end of the sample. At the end of 2021, the contributions of aggregate supply shocks to inflation dynamics were of a similar order of magnitude as those associated with uncertainty shocks, while the contributions of aggregate demand shocks were substantially smaller.

The paper is structured as follows: The following section II provides a review of the related literature. Section III describes our empirical approach. Section IV presents the results and section V supports our findings with a number of robustness checks. Section VI concludes the paper.

[1]Our analysis complements papers that analyse the first few months of the COVID-19 period (e.g. Bekaert, Engstrom, and Ermolov, 2020), or use pre-crisis data to obtain model-implied predictions for the decline in output and prices during the pandemic itself (e.g. Baker *et al.*, 2020a).

[2]Similar in spirit, Ludvigson *et al.* (2021) use narrative restrictions to separate real activity shocks from financial and macroeconomic uncertainty shocks. Antolín-Díaz, Petrella, and Rubio-Ramírez (2021) consider narrative restrictions to render anticipated and unanticipated shocks orthogonal.

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II. Related literature

Our paper is closely related to the growing literature that distinguishes between supply and demand effects associated with the COVID-19 pandemic. Based on a large-scale micro-founded model, Baqaee and Farhi (2022) conclude that supply and demand shocks each account for about half of the downturn in US real GDP between February and May 2020. Using survey data collected at the firm level in April and May 2020, Balleer *et al.* (2023) find a 10% increase in the probability of a price decrease by German firms, relative to a scenario without COVID-19. And since firms report lacking demand as the main cause of the adverse effects, they interpret this result as evidence in favour of the view that aggregate demand effects dominate aggregate supply effects. Bekaert *et al.* (2020) use non-Gaussian characteristics of US macroeconomic forecast revisions from 1968Q4 to 2019Q2 to identify aggregate demand and supply shocks and predict how they contributed to the recession that started with the COVID-19 pandemic. Their analysis suggests that the initial decline in GDP was mainly due to aggregate demand shocks, while aggregate supply shocks became more important relatively soon after the initial decline. Shapiro (2022) uses an approach that is methodologically related to our analysis to decompose US inflation dynamics into demand-driven and supply-driven components and finds that the surge in inflation in the spring of 2021 was primarily demand-driven. We contribute to this branch of the literature by characterizing contributions associated with supply-side and demand-side shocks for the initial downturn as well as for the subsequent recovery, and we explicitly study the role of uncertainty shocks.

Brinca, Duarte, and Faria-e Castro (2021) focus on the labour market and identify labour demand and supply shocks. They find that about two-thirds of the decline in the growth rate of hours worked in March and April 2020 was due to labour supply shocks, although the magnitudes differed strongly across sectors. Coibion, Gorodnichenko, and Weber (2020b) evaluate the labour market effect of the pandemic based on household survey data. They find that, besides a relatively small increase in the unemployment rate of 2 percentage points, the participation rate decreased by about 7 percentage points until early April 2020. Related to that, Coibion, Gorodnichenko, and Weber (2020a) state that more than 50% of the survey participants report declines in income or wealth due to COVID-19 and that consumer spending declined by 31 log percentage points.

Several contributions stress the role of uncertainty during the COVID-19 pandemic. Dietrich *et al.* (2022) use US household survey data and document a high dispersion in households' expectations of the output and inflation effects associated with COVID-19, which suggests a high degree of uncertainty. Based on an identification by heteroscedasticity approach, Miescu and Rossi (2021) find that a COVID-19-induced shock leads to a decline in economic activity, tightening financial conditions, and an increase in uncertainty. In line with our characterisation of uncertainty shocks, Miescu and Rossi (2021) conclude that these patterns closely resemble the responses to an uncertainty-induced shock. Caggiano, Castelnuovo, and Kima (2020) use global data from 1990M1 to 2020M4 and identify an uncertainty shock in a VAR. They conclude that an uncertainty shock of a similar size as observed during the COVID-19 downturn leads to a peak decline in world industrial production of about 1.5%. Baker *et al.* (2020a) use the instrument described in Baker, Bloom, and Terry (2023) to estimate the effects of the

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pandemic on US output.[3] Their exercise suggests that about half of the forecasted output contraction can be attributed to COVID-19-induced uncertainty. Our analysis differs from these contributions in terms of the empirical approach, the identification strategy, and in terms of our focus on the relative importance of uncertainty shocks when compared to other macroeconomic shocks pertaining to the pandemic.

III. Empirical approach

We study the macroeconomic drivers of changes in output growth and inflation during the COVID-19 recession using structural VAR analysis. In this section, we describe the specification of the VAR model, our identification approach, and the estimation of the model.

VAR model and specification

We estimate the following reduced-form VAR model

$$\boldsymbol{y}_t = \boldsymbol{c} + \sum_{l=1}^{p} \boldsymbol{B}_l \boldsymbol{y}_{t-l} + \boldsymbol{u}_t, \qquad \text{for } 1 \leq t \leq T, \tag{1}$$

where $\boldsymbol{y}_t$ is an $n \times 1$ vector of endogenous variables, $\boldsymbol{c}$ is a $n \times 1$ vector of parameters of constants, $\boldsymbol{B}_l$ is an $n \times n$ matrix of parameters at lag l for $1 \leq l \leq p$ and p is the lag length. Further, $\boldsymbol{u}_t$ is a $n \times 1$ vector of reduced-form innovations with $\boldsymbol{u}_t \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{\Sigma})$, where $\boldsymbol{\Sigma}$ is the $n \times n$ variance-covariance matrix, and T is the sample size.

As in Altig *et al.* (2020) and Baker, Bloom, and Davis (2016), we use monthly measures of uncertainty, economic activity, financial markets, and the monetary policy stance in the vector of endogenous variables. In particular, $\boldsymbol{y}_t$ includes the S&P 500 stock market volatility index (VIX), the year-on-year change in industrial production (IP), Gilchrist and Zakrajsek's (2012) excess bond premium (EBP), and the 1-year Treasury Bill (1-Y TB) rate. Additionally, we also consider the year-on-year inflation rate (INFL) based on the consumer price index. Table 1 provides more detailed variable descriptions and data sources. We set $p = 12$ in the baseline estimation.[4] The sample runs from January 1990 to December 2021.[5]

Identification

The structural VAR implied by equation (1) is

$$\boldsymbol{A}_0 \boldsymbol{y}_t = \boldsymbol{v} + \sum_{l=1}^{p} \boldsymbol{A}_l \boldsymbol{y}_{t-l} + \boldsymbol{\epsilon}_t, \qquad \text{for } 1 \leq t \leq T, \tag{2}$$

[3] Baker *et al.* (2023) use events such as natural disasters, terrorist attacks, or political shocks as an instrument for the uncertainty shock. Their analysis was first circulated as a working paper (see Baker, Bloom, and Terry, 2020b).

[4] In section V we show that our main findings are robust to alternative model specifications and data transformations.

[5] We choose the sample start in January 1990 due to missing data before that date.

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TABLE 1
Variable description

Name	*Variable*	*Source*	*Code/Vintage*
IP	Year-on-year change in industrial production (total index, 2012 = 100, seasonally adjusted)	FRED	INDPRO
INFL	Year-on-year change in the consumer price index (total all items for the USA, 2015 = 100, seasonally adjusted)	FRED	CPALTT01USM661S
1-Y TB Rate	One-year Treasury constant maturity rate (not seasonally adjusted)	FRED	GS1
EBP	Updated excess bond premium series	Favara *et al.* (2016)	ebp
VIX	CBOE volatility index (not seasonally adjusted, monthly average)	FRED	VIXCLS
EPU Index	Economic Policy Uncertainty (not seasonally adjusted, monthly average)	FRED	USEPUINDXD
TM UNC	Updated total macro uncertainty index ($h = 1$, $h = 12$)	Jurado, Ludvigson, and Ng (2015)	06-2021
EC UNC	Updated economic macro uncertainty index ($h = 1$)	Jurado *et al.* (2015)	06-2021
TF UNC	Updated total financial uncertainty index ($h = 1$)	Jurado *et al.* (2015)	06-2021
UNEMP Rate	Unemployment rate (percent, seasonally adjusted)	FRED	UNRATE
CFNAI	Chicago Fed national activity index (not seasonally adjusted)	FRED	CFNAI
PC EXP	Personal Consumption Expenditures (seasonally adjusted annual rate)	FRED	PCE

Notes: Federal Reserve Economic Data (FRED); updated and extended uncertainty measures are available at https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes.

where $\boldsymbol{A}_l = \boldsymbol{A}_0\boldsymbol{B}_l$ for $1 \leq l \leq p$, $\boldsymbol{v} = \boldsymbol{A}_0\boldsymbol{c}$, and $\boldsymbol{\epsilon}_t = \boldsymbol{A}_0 u_t$ with $\boldsymbol{\epsilon}_t \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{I}_n)$, where $\boldsymbol{I}_n$ is the $n \times n$ identity matrix. As is well-known, $\boldsymbol{\Sigma} = E(\boldsymbol{u}_t\boldsymbol{u}_t') = (\boldsymbol{A}_0\boldsymbol{A}_0')^{-1}$ and thus, $\boldsymbol{A}_0$ is underdetermined and identification restrictions are necessary to obtain the structural parameters. Building on Faust (1998), Canova and Nicoló (2002), and Uhlig (2005), we follow Antolín-Díaz and Rubio-Ramírez (2018) and impose an arguably weak set of economically plausible identification restrictions. Specifically, we consider classical sign restrictions placed on impulse response functions together with narrative sign and magnitude restrictions placed on the identified shocks and the historical decomposition. Table 2 summarizes our identifying assumptions.

The sign restrictions on the impulse response function for aggregate supply and aggregate demand shocks are standard and consistent with the predictions of a large number of macroeconomic models (see e.g. Fry and Pagan, 2011; Furlanetto *et al.*, 2017; Calvert Jump and Kohler, 2022). In response to an adverse aggregate demand shock, economic activity and inflation decline. We thus restrict IP growth and inflation to decrease. According to a standard Taylor rule, the central bank responds to this shock by lowering the interest rate. Hence, we restrict the 1-year Treasury Bill rate to go down. Standard macroeconomic models predict that aggregate supply shocks, that is exogenous shifts of the Phillips curve, such as price mark-up shocks, wage mark-up shocks, or

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TABLE 2
Identification restrictions

(A) Sign restrictions on impulse response functions

Shocks	*IP growth*	*INFL*	*1-Y TB Rate*	*VIX*	*EBP*
Aggregate demand shock	≤ 0	≤ 0	≤ 0		
Aggregate supply shock	≤ 0	≥ 0			
Uncertainty shock	≤ 0	≤ 0	≤ 0		

(B) Narrative sign and magnitude restrictions on identified shocks and historical contributions

Shock	*Date*	*Restriction*
Uncertainty shock	September 2008	Shock is negative (contractionary) and has the largest positive effect on the VIX
	July 2011	Shock is negative and has a positive effect on the VIX
	August 2011	Shock is negative and has a positive effect on the VIX

Notes: Dates for narrative sign restrictions of the uncertainty shock follow Ludvigson *et al.* (2021); sign restrictions are imposed on impact and the subsequent month. All shocks are normalize to be contractionary, that is, to affect IP growth negatively on impact.

technology shocks (see e.g., Smets and Wouters, 2007), move economic activity and inflation in opposite directions. In line with this prediction, we restrict IP growth to decrease and inflation to increase. All sign restrictions are imposed on impact and the subsequent month.

Leduc and Liu (2016) argue that uncertainty shocks are essentially specific examples of aggregate demand shocks. Following this logic, we assume that uncertainty shocks represent, at the aggregate level, a subset of general aggregate demand shocks and we therefore impose the same sign restrictions on the impulse response functions. Nevertheless, since we require uncertainty shocks to be orthogonal, we disentangle uncertainty shocks from other aggregate demand shocks that are unrelated to uncertainty by imposing additional narrative sign restrictions as in Ludvigson *et al.* (2021). These non-uncertainty aggregate demand shocks represent, for example consumer preference shocks or exogenous spending shocks.

We impose the narrative restrictions in months during which uncertainty was particularly high (see also Baker *et al.*, 2023). Following Ludvigson *et al.* (2021), we assume that uncertainty shocks were particularly pronounced in September 2008, when Lehman collapsed and the Dow Jones Index dropped by roughly 50% over the next 17 months. Thus, we impose the restriction that the uncertainty shock gave rise to the largest effect on the VIX during this month and that the VIX increased in response to this shock.[6] Moreover, as in Ludvigson *et al.* (2021), we assume that uncertainty shocks were negative (contractionary) during the 2011 debt-ceiling crisis in the U.S. Thus, we restrict the identified uncertainty shocks to be negative and that they give rise to an increase in the VIX in July and August 2011.

[6]Note that while the narrative magnitude restriction is imposed on the VIX, as a frequently used observable indicator of uncertainty, the shocks to uncertainty are not identified through variations in the VIX, as it is the case in for example recursively identified VARs. In section V we explore the robustness of our results with respect to different indicators of economic uncertainty.

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Formally, let $\mathbf{\Phi}_h$ be a $n \times n$ matrix of structural impulse responses, where $\phi_{i,j,h}$, the element in row i and column j, captures the response of the ith variable to the jth structural shock at horizon h for $0 \leq h \leq H$ with H being the maximum impulse horizon. Further, let h^s be the horizons for which the sign restrictions are imposed, and $F(\mathbf{\Phi}_{h^s})$ be the vertically stacked impulse responses at horizons h^s with dimension $nh^s \times n$. Then, following Arias, Rubio-Ramírez, and Waggoner (2018) the sign restrictions on the impulse responses can be represented by the function

$$\boldsymbol{S}_j F(\mathbf{\Phi}_{h^s})\boldsymbol{e_j} > 0, \tag{3}$$

where $\boldsymbol{S}_j$ is a $r_j \times nh^s$ selection matrix for each structural shock j with one sign restriction in each row and the columns correspond to the impulse response of variable i at horizon h^s.[7] $\boldsymbol{e_j}$ is the *j-th* column of $\boldsymbol{I}_n$ selecting the sign-restricted impulse responses to the structural shock j.

As in Antolín-Díaz and Rubio-Ramírez (2018), the narrative sign restrictions on the structural shocks are directly imposed on the identified shocks $\boldsymbol{\epsilon}_t$ as

$$\boldsymbol{s}_j \boldsymbol{\epsilon}_j > 0, \tag{4}$$

where $\boldsymbol{s}_j$ is a $1 \times T\text{-}p$ selection vector for each structural shock j with 1s and -1s at the respective time period t. Moreover, we impose narrative sign and magnitude restrictions on the historical contributions of the identified shocks. The historical contribution of the jth structural shock on the unexpected change in the ith variable at time t is given by $\phi_{i,j,0}\epsilon_{j,t}$, the impact response of variable i to shock j times the shock j at time t. We impose restrictions such that the jth structural shock accounts for a positive/negative contribution on the ith variable and induces the largest absolute contribution as compared to the absolute contributions of all other shocks $\boldsymbol{\epsilon}_k$, where $k = 1, \ldots, n$ and $k \neq j$. These restrictions can be imposed as

$$\boldsymbol{s}_j \phi_{i,j,0} \boldsymbol{\epsilon}_j > 0, \quad \text{and} \tag{5}$$

$$|\boldsymbol{s}_j \phi_{i,j,0} \boldsymbol{\epsilon}_j| - \max\left(|\boldsymbol{s}_j \boldsymbol{\phi}_{i,k,0} \boldsymbol{\epsilon}_k|\right) > 0, \tag{6}$$

where $\boldsymbol{s}_j$ selects the historical contribution at time t with the respective sign, and $|\cdot|$ captures the absolute value.

Estimation and priors

We estimate equation (1) using standard Bayesian methods as described in Rubio-Ramírez, Waggoner, and Zha (2010) and Arias *et al.* (2018). In particular, we use flat priors for the reduced-form parameters $(\boldsymbol{B}_i, \boldsymbol{\Sigma})$ in Equation (1) and sample first from the posterior of the reduced-form VAR. Secondly, we map the reduced-form draws into the structural parameterisation using a random orthogonalisation of the reduced-form innovations $\boldsymbol{u}_t$.

[7] We refer to a matrix (vector) as a selection matrix (vector) if all entries are equal to zero except those that are explicitly set to -1 or 1.

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To obtain a random orthogonalization, we combine a Cholesky decomposition of the reduced-form variance-covariance matrix $\boldsymbol{\Sigma}$ with a random orthonormal $n \times n$ matrix $\boldsymbol{Q}$, that is, $\boldsymbol{\epsilon}_t = \boldsymbol{Q}\boldsymbol{P}^{-1}\boldsymbol{u}_t$, where $\boldsymbol{P}$ is the lower triangular Cholesky factor, $\boldsymbol{\Sigma} = \boldsymbol{P}\boldsymbol{P}'$, and $\boldsymbol{X} = \boldsymbol{Q}\boldsymbol{R}$ with the elements of the $n \times n$ matrix $\boldsymbol{X}$ being independent draws from the standard normal distribution and the diagonal elements of $\boldsymbol{R}$ are normailize to be positive.

Finally, we follow Antolín-Díaz and Rubio-Ramírez (2018) and reweigh the posterior distribution of the structural parameters, as sign and magnitude restrictions on the structural shocks and historical decomposition, as described in equations (4) to (6), truncate the likelihood function of the reduced-form parameters. In particular, we reweigh each draw that satisfies the imposed restrictions by $1/\omega$, where we approximate ω by simulating M random draws of $\boldsymbol{\epsilon}_t$ from the standard normal distribution and calculating the proportion of the M draws that satisfy the narrative restrictions. We set $M = 1,000$. Antolín-Díaz and Rubio-Ramírez (2018) show that with this estimation routine we effectively draw from the uniform-normal-inverse-Wishart posterior of $(\boldsymbol{B}_i, \boldsymbol{\Sigma}, \boldsymbol{Q})$ conditional on the imposed restrictions.[8]

IV. Results

Figure 1 shows the impulse responses to the identified shocks. The responses to aggregate demand and aggregate supply shocks are fairly standard. Uncertainty shocks affect IP growth rather persistently for approximately 1 year. Even though sign restrictions on AD and uncertainty shocks are identical, uncertainty shocks have more distinct effects on macroeconomic aggregates and especially on the VIX. Interestingly, uncertainty shocks also exert the strongest effect on the EBP, indicating that financial frictions are an important element of the propagation mechanism for uncertainty (see e.g. Alessandri and Mumtaz, 2019).[9]

We are primarily interested in the time-varying contributions of each of the three identified shocks to output growth and inflation dynamics during the pandemic. Figure 2 shows the historical decomposition for the year-on-year growth rate of industrial production.[10] We see that even before the sharp decline in IP growth in March 2020, aggregate supply and aggregate demand shocks contributed slightly negatively. Uncertainty shocks, in contrast, contributed marginally positively to IP growth.

Although the contributions of all three identified shocks became increasingly negative from March 2020 onward, this phase of the pandemic was mainly driven by uncertainty shocks. While containment measures, for instance, are likely to have induced adverse

[8]Noteworthy, the uniform prior over $\boldsymbol{Q}$ does not imply that the elements of $\boldsymbol{Q}$ are uniformly distributed and as we follow a set-identification approach the distribution of the elements of $\boldsymbol{Q}$ influences the posterior distribution of the impulse responses (Baumeister and Hamilton, 2015).

[9]As suggested in for example Uhlig (2017), we follow the common Bayesian approach and summarize the marginal posterior distributions of the impulse response functions by showing the median and percentiles at each horizon. To ensure that the set of identified models contains the point estimates, we show the results based on one unique model draw, which we select using the squared-loss function proposed in Inoue and Kilian (2022), in section V.

[10]The historical decomposition of the *i-th* variable at time t shows the cumulative contribution of the jth shock from the start of the sample up to t. Formally, this is given by $y_{i,j,t} = \sum_{h=0}^{t-1} \phi_{i,j,h}\epsilon_{j,t-h}$ (see e.g. Burbidge and Harrison, 1985). We do not present contributions of the residual shocks, as they do not allow for a structural interpretation.

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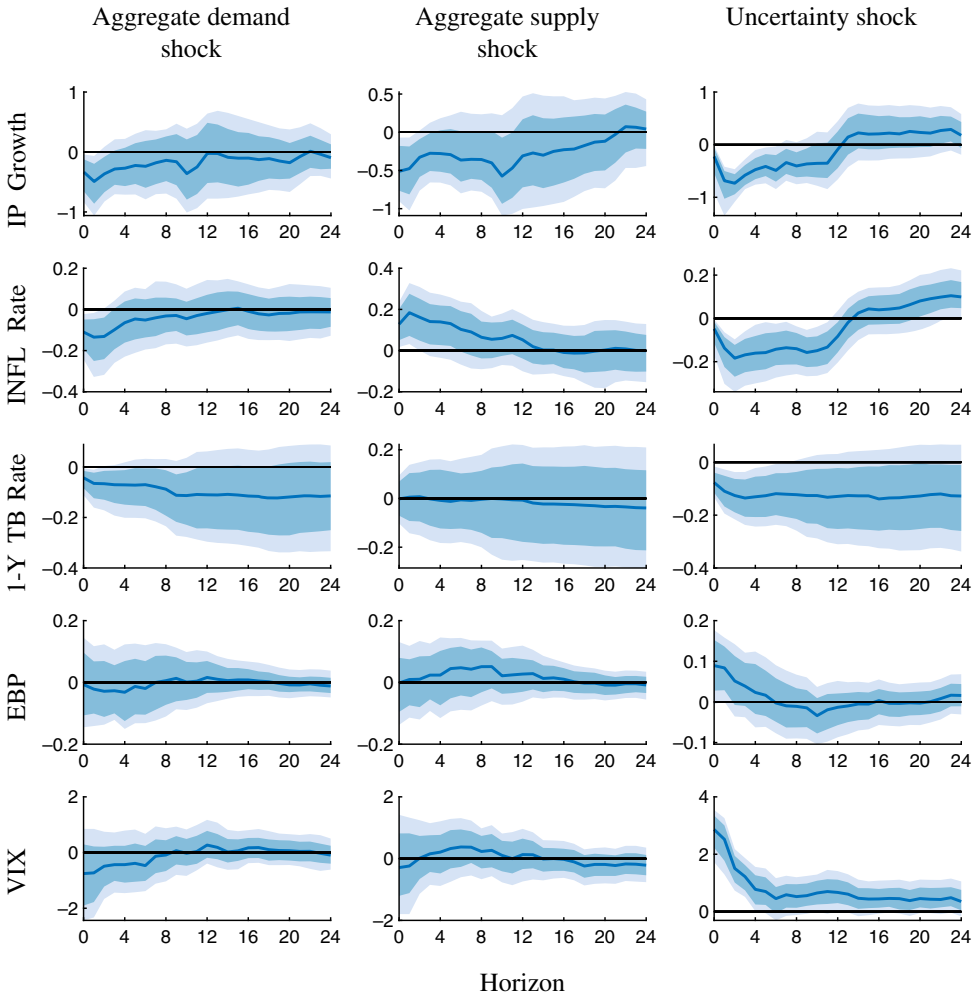


Figure 1. Impulse responses to aggregate demand, aggregate supply, and uncertainty shocks.
Notes: The figure shows the point-wise posterior medians of the impulse responses (solid lines) together with 90% and 68% centered point-wise credibility bands (light and dark shaded areas). 'IP Growth' stands for the year-on-year change in industrial production, 'INFL Rate' for the year-on-year inflation rate based on the consumer price index, '1-Y TB Rate' for the 1-year Treasury Bill rate, 'EBP' for Gilchrist and Zakrajsek's (2012) excess bond premium, and 'VIX' for the S&P 500 stock market volatility index. [Colour figure can be viewed at *wileyonlinelibrary.com*]

aggregate supply and demand effects, the strongest contribution to the decline came from increased uncertainty. Thus, as the future consequences of the pandemic were difficult to foresee, agents acted presumably in a precautionary way and were reluctant to take decisions that may have been costly to reverse, such as investment and hiring decisions, ultimately leading to the decline in aggregate demand.

Around April 2020 the negative contributions of all three shocks started to decline in magnitude. While the contributions of AD shocks faded out, AS shocks remained quantitatively important throughout 2020. This result suggests that supply-side factors, such as supply chain disruptions, had more persistent effects on output dynamics.

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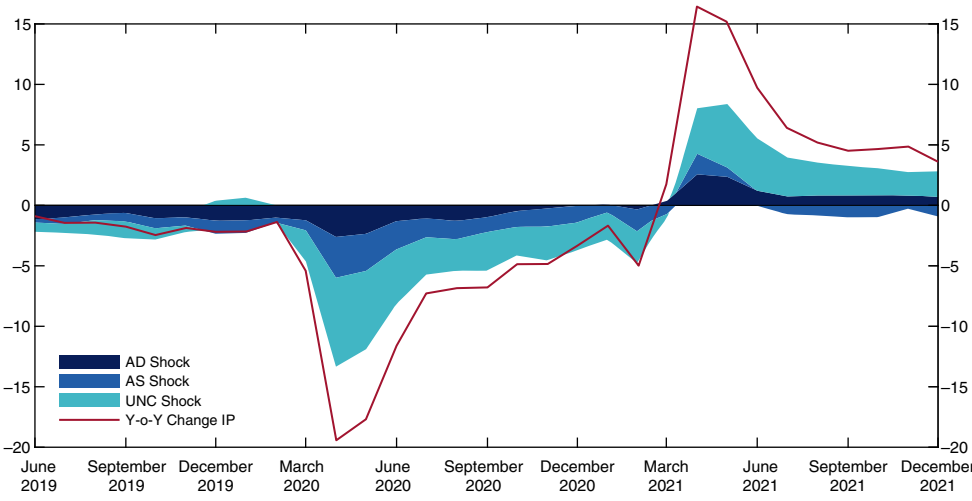


Figure 2. Historical decomposition of industrial production growth during the COVID-19 pandemic (2019M6-2021M12).
Notes: The figure shows point-wise posterior medians of the historical decomposition of the year-on-year change in industrial production (stacked areas) for aggregate demand ('AD'), aggregate supply ('AS'), and uncertainty ('UNC') shocks, together with the change in industrial production (solid line). Values are reported in percent. [Colour figure can be viewed at *wileyonlinelibrary.com*]

Similarly, uncertainty shocks contributed to output dynamics throughout 2020 and were the main source of negative contributions.

In early 2021, IP growth turned positive, when a strong base effect occurred, and although the growth rate declined again towards the end of 2021, it remained positive. During this phase, it was again uncertainty shocks that exerted the most pronounced contribution to output dynamics.

Next, we turn to the historical decomposition of the CPI inflation rate in Figure 3. Similar to what we find for output dynamics, the sharp decline in the inflation rate in March 2020 was largely driven by uncertainty shocks, which exerted persistent downward pressure throughout 2020. And while adverse aggregate demand shocks also contributed to the decline in inflation, aggregate supply shocks exerted pronounced inflationary effects. In March 2021, the contributions of aggregate demand and uncertainty shocks turned positive and although the contribution of non-uncertainty-related AD shocks declined again over time, the contributions of uncertainty shocks remained substantial. AS shocks started to exert more pronounced inflationary effects during the second half of 2021. While these findings suggest that supply-side factors became particularly relevant for inflation dynamics during this later phase, the contributions of uncertainty shocks were still of a similar order of magnitude as those associated with aggregate supply shocks throughout 2021.

V. Robustness analysis

In this section, we perform a number of robustness checks to support our results. In particular, we consider alternative measures of economic activity, different proxies for uncertainty, alternative identification strategies, and different model specifications.

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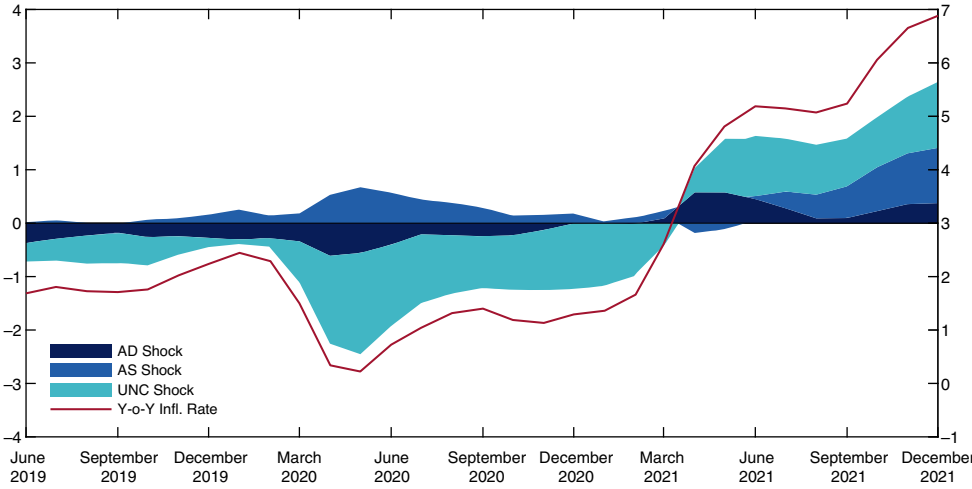


Figure 3. Historical decomposition of the inflation rate during the COVID-19 pandemic (2019M6-2021M6). *Notes*: The figure shows point-wise posterior medians of the historical decomposition of the year-on-year inflation rate (stacked areas, left axis) for aggregate demand ('AD'), aggregate supply ('AS'), and uncertainty ('UNC') shocks, together with the inflation rate (solid line, right axis). Values are reported in percent. [Colour figure can be viewed at *wileyonlinelibrary.com*]

Different economic activity measures

In the first robustness checks, we consider alternative measures of real activity. More specifically, we use the unemployment rate, the Chicago Fed national activity index (CFNAI), and consumption expenditures, instead of IP. We see from Figure 4 that the contributions follow largely similar patterns as in our baseline analysis.

Different uncertainty measures

While we use the VIX index as a proxy for uncertainty in the baseline analysis, alternative measures are frequently used in the literature. Thus, we test if our results are robust to the choice of the uncertainty proxy by using the economic policy uncertainty (EPU) index (Baker *et al.*, 2016) and updated versions of the total macro uncertainty index, the economic macro uncertainty index, and the total financial uncertainty index as computed in Jurado *et al.* (2015) as a measure for uncertainty. Figure 5 presents the contributions of aggregate demand (Panel a), aggregate supply (Panel b), and uncertainty shocks (Panel c) to the year-on-year change in industrial production during the COVID-19 pandemic based on models using these alternative uncertainty measures. In addition, each panel illustrates the baseline contributions of these shocks along with the corresponding 68% credible sets. The figure shows that the contributions of aggregate demand and aggregate supply shocks are robust to the choice of the uncertainty measure. And although the results based on the updated uncertainty measures of Jurado *et al.* (2015) suggest that uncertainty shocks exerted increasingly negative contributions already before the onset of the COVID-19 pandemic, the overall patterns are still similar to our baseline results and, importantly, the contributions of uncertainty shocks exceed those of aggregate demand and aggregate supply shocks in magnitude.

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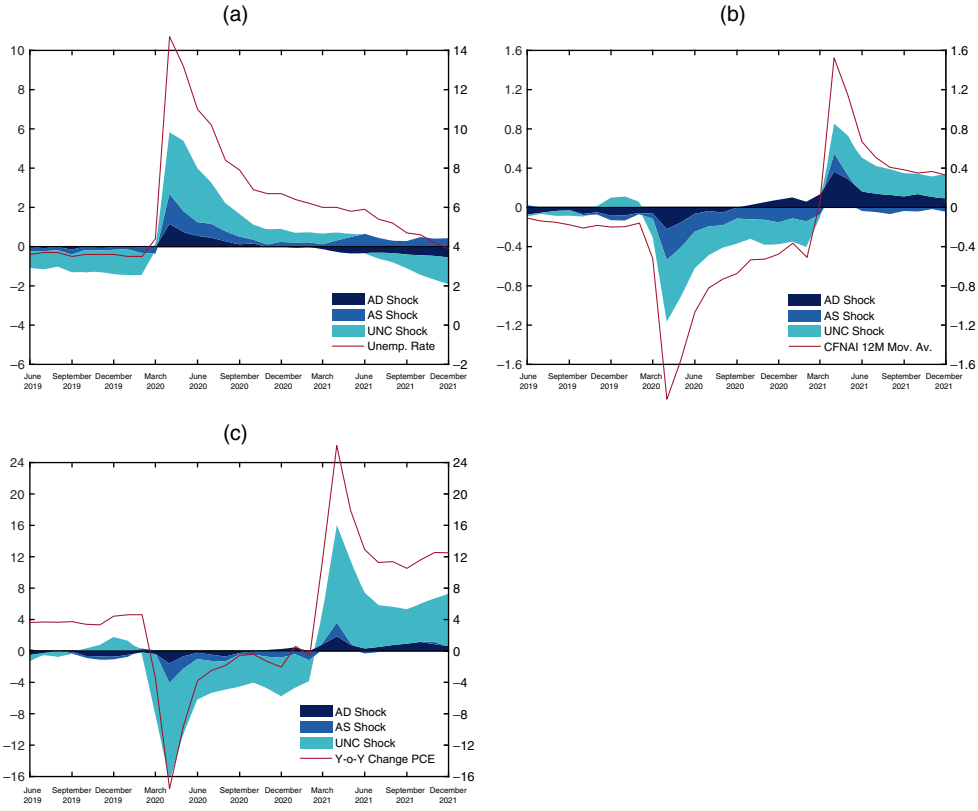


Figure 4. Different economic activity measures.
Notes: The figure shows point-wise posterior medians of the historical decomposition of different economic activity measures (stacked areas, left axes) for aggregate demand ('AD'), aggregate supply ('AS'), and uncertainty ('UNC') shocks, together with the respective output measure (solid lines, right axes). For better comparability with our baseline results we use a 12-month backward looking moving average of the Chicago Fed national activity index (CFNAI). Please refer to Table 1 for additional information about the output measures. Values are reported in percent. (a) Unemployment rate; (b) CFNAI (12-month moving average); (c) Personal consumption expenditures (year-on-year change). [Colour figure can be viewed at *wileyonlinelibrary.com*]

Alternative identifying assumptions and model selection

Next, we check the sensitivity of our results with respect to the identification scheme. We consider alternative horizons for the sign restrictions placed on impulse response functions and we impose additional narrative sign restrictions on the structural shocks. More precisely, we specify sign restrictions (i) on impact only and (ii) on impact and the three subsequent months.

To check the robustness of our results with respect to the narrative restrictions, we first add narrative restrictions for the identification of the aggregate demand and aggregate supply shocks. Ludvigson *et al.* (2021) assume that the sum of real shocks during the Great Recession period (2007M12-2009M6) is negative, that is, these shocks exert contractionary effects. Accordingly, we impose the restriction that aggregate demand and aggregate supply shocks are in sum negative during this period: $\text{sum}(\boldsymbol{s}_{j,t,t+h}\boldsymbol{\epsilon}_j) > 0$,

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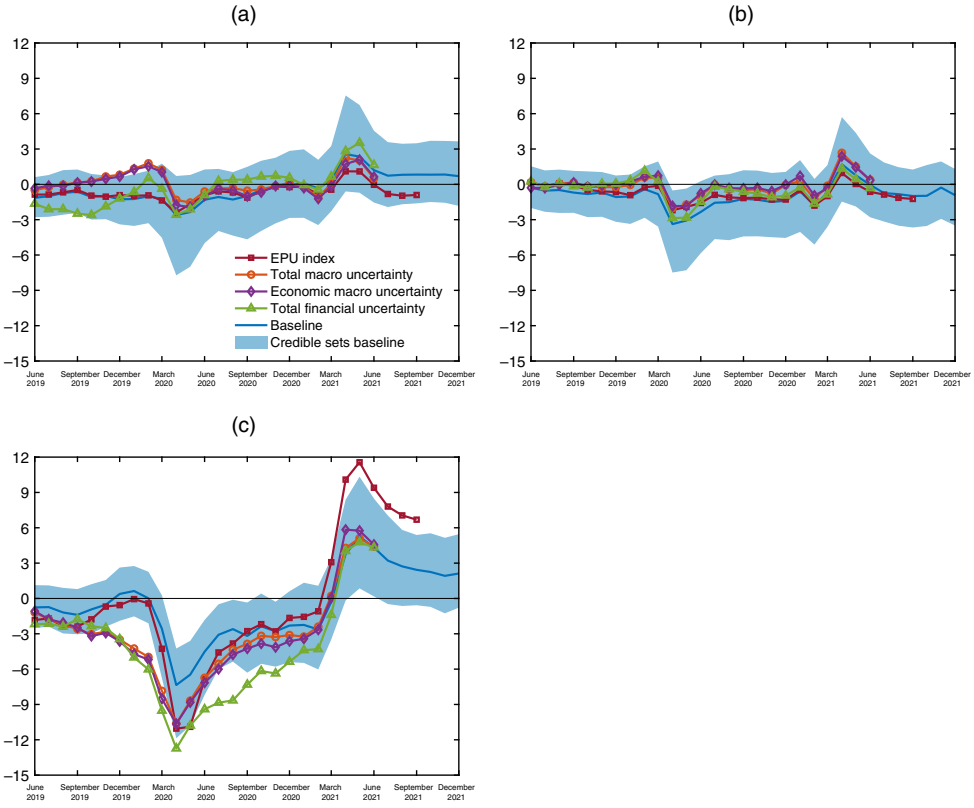


Figure 5. Different uncertainty measures.
Notes: The figure shows point-wise posterior medians of the historical decomposition of the year-on-year change in industrial production from our baseline specification (solid lines without markers) together with 68% centred point-wise credibility bands (shaded areas), and point-wise posterior medians from the following robustness checks (solid lines with markers): In the specification labelled 'EPU' we use the economic policy uncertainty index as uncertainty measure; in 'Total macro uncertainty' we use the updated macroeconomic uncertainty measure; in 'Economic macro uncertainty' we use the updated macroeconomic uncertainty measure excluding health related uncertainty, and in 'Total financial uncertainty' we use the updated financial uncertainty measure. Values are reported in percent. (a) Aggregate demand shock; (b) aggregate supply shock; (c) Uncertainty shock. [Colour figure can be viewed at *wileyonlinelibrary.com*]

where t and $t+h$ correspond to December 2007 and June 2009, respectively. Second, we impose the restriction that the Brexit vote in June 2016 was associated with negative uncertainty shocks. According to Piffer and Podstawski (2017), who construct an indicator for exogenous uncertainty shocks, the Brexit vote represents the largest contractionary uncertainty event before the outbreak of the COVID-19 pandemic.[11] Since this more recent event may help to improve the identification of the uncertainty shocks during the COVID-19 recession, we impose the additional narrative sign restriction that the uncertainty shock was negative in June 2016. Finally, we present point estimates of the historical decomposition calculated with the impulse responses of one unique model draw.

[11]The indicator, which builds on Bloom (2009), is available at https://sites.google.com/site/michelepiffereconomics (accessed in November 2022).

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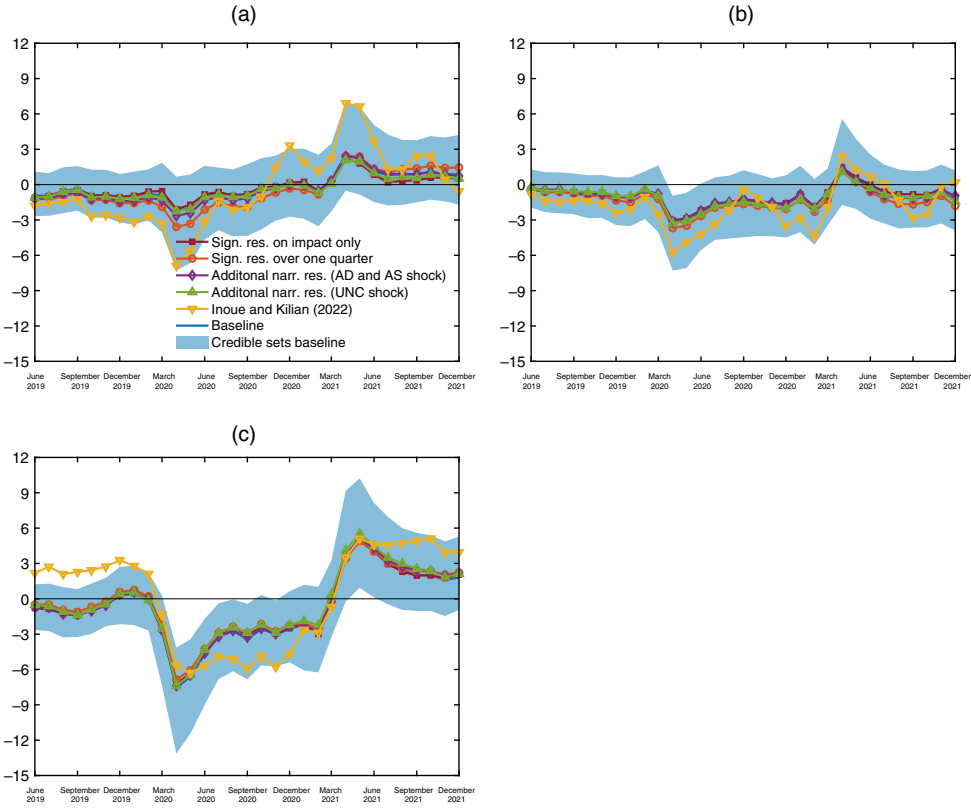


Figure 6. Alternative identifying assumptions and model selection.
Notes: The figure shows point-wise posterior medians of the historical decomposition of the year-on-year change in industrial production from our baseline specification (solid lines without markers) together with 68% centred point-wise credibility bands (shaded areas), and point-wise posterior medians from the following robustness checks (solid lines with markers): In the specification labelled 'Sign. res. on impact only' we impose the sign restrictions on the impulse response functions only at horizon zero; in 'Sign. res. over one quarter' we impose the sign restrictions on the impulse response functions up to horizon three; in 'Additional narr. res. (AD and AS shock)' we impose the additional narrative sign restrictions that aggregate demand and aggregate supply shocks are overall negative (contractionary) during the Great Recession period (2007M12-2009M6); in 'Additional narr. res. (UNC shock)' we impose the additional narrative sign restriction that uncertainty shocks are negative in June 2016, that is the month on the Brexit vote; and in 'Inoue and Kilian (2022)' we show point estimates calculated based on the impulse responses of one structural model, which we select using the squared loss-function described in Inoue and Kilian (2022) evaluated over the impulse responses of the identified shocks and horizons $h = 0, 1, \ldots, 12$. Values are reported in percent. (a) Aggregate demand shock; (b) aggregate supply shock; (c) Uncertainty shock. [Colour figure can be viewed at *wileyonlinelibrary.com*]

As proposed in Inoue and Kilian (2022), we select the model draw using a squared loss function to ensure that the point estimates are contained in the set of identified models.

Figure 6 shows the shock contributions to industrial production for these alternative identification schemes and model selection strategies. For all three shocks, the results closely resemble our baseline results, as the contributions are within the 68% credible sets throughout the pandemic and the recovery period. This is also the case for the uncertainty shock, where the contributions to the dynamics of output growth based on the model selected using Inoue and Kilian's (2022) squared loss function are outside of the 68%

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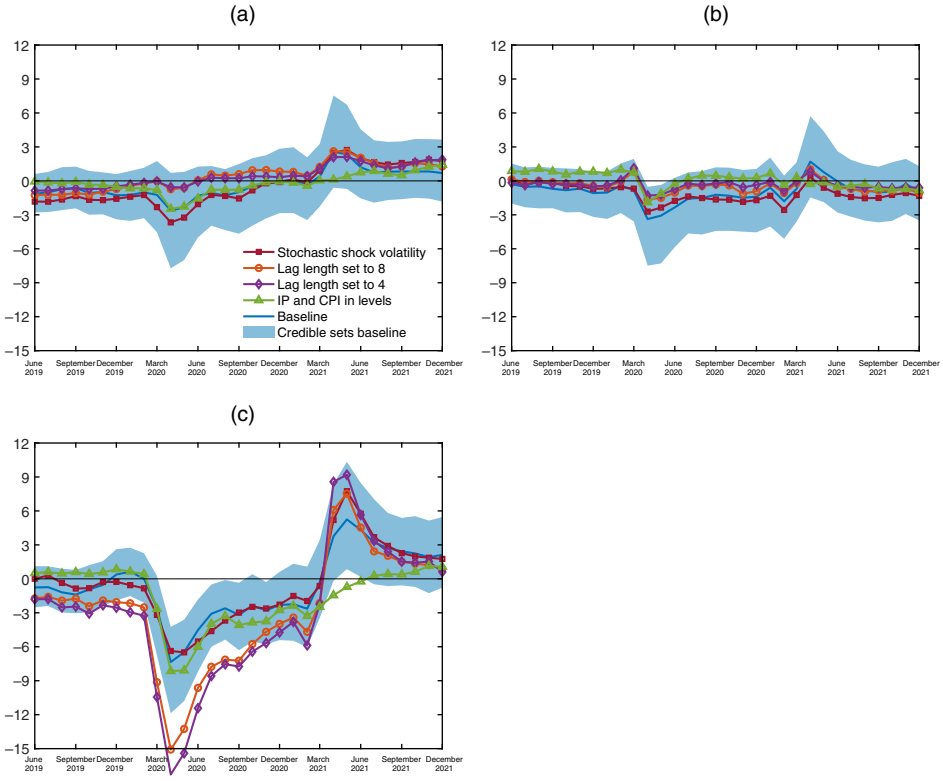


Figure 7. Alternative model specifications.
Notes: The figure shows point-wise posterior medians of the historical decomposition of the year-on-year change in industrial production from our baseline specification (solid lines without markers) together with 68% centred point-wise credibility bands (shaded areas), and point-wise posterior medians from the following robustness checks (solid lines with markers): In the specification labelled 'Stochastic shock volatility' we allow for time-varying shock volatility; in 'Lag length set to 84' we set the maximum lag length p to 8 and 4, respectively, and in 'IP and CPI in levels' we consider industrial production and the consumer price index in log levels. Values are reported in percent. (a) Aggregate demand shock; (b) aggregate supply shock; (c) Uncertainty shock. [Colour figure can be viewed at *wileyonlinelibrary.com*]

credible sets for the period before the start of the pandemic. They are nevertheless in line with our baseline results for the downturn and the recovery associated with the pandemic.

Alternative model specifications

In the last part of the robustness section, we employ alternative specifications of the data generating process to check the robustness of our findings also in that direction. Specifically, we consider models with four (respectively eight) autoregressive lags and a model with industrial production and the consumer price index in levels instead of year-on-year changes. In addition, we follow Chan (2021) and estimate a model that allows for time variation in the volatility of the VAR innovations. While the contributions of aggregate demand and aggregate supply shocks to industrial production in Panels a and b of Figure 7 are always within the 68% credible set of the baseline results, the contributions of the uncertainty shock based on the models with fewer autoregressive lags

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suggest an even stronger negative contribution to the decline in industrial production after the onset of the COVID-19 pandemic than in the baseline model.

To summarize, all sensitivity checks support the conclusion that uncertainty shocks were the main driver of the contraction in output during the pandemic, while aggregate demand and supply shocks contributed to a lesser degree.

VI. Concluding remarks

The COVID-19 pandemic was associated with a severe economic contraction. In this paper, we identify aggregate supply shocks, aggregate demand shocks, and uncertainty shocks and calculate historical decompositions to explore how strongly the individual shocks contributed to output growth and inflation dynamics during the COVID-19 pandemic. This exercise allows us to sequence the COVID-19 recession in the USA in the sense of evaluating the contributions of the different macroeconomic shocks that gave rise to the recession and to the subsequent recovery.

Since we characterize uncertainty shocks as disturbances to aggregate demand, our findings suggest that it was overall a decline in aggregate demand that dominated output and inflation dynamics during the early phase of the pandemic, which corroborates the view that the COVID-19 recession was mainly demand-driven (see e.g. Bekaert *et al.*, 2020; Shapiro, 2022; Balleer *et al.*, 2023). Although uncertainty has been emphasized in the existing literature as a key driver of the sharp and swift downturn associated with the pandemic (see e.g. Caggiano *et al.*, 2020; Baker *et al.*, 2020a; Miescu and Rossi, 2021; Dietrich *et al.*, 2022), we provide new insights by quantifying the contributions of uncertainty shocks relative to other macroeconomic drivers. In particular, our results suggest that relative to aggregate supply and non-uncertainty-related aggregate demand shocks, uncertainty shocks exerted the strongest effects during the downturn.

Moreover, we are able to characterize how the relative contributions of identified shocks evolved over time as we do not only scrutinize the downturn but also the subsequent recovery phase. We find that declining uncertainty played a crucial role during the acceleration of economic activity that followed the recession. Thus, uncertainty shocks did not only cause substantial disruptions of economic activity, declining uncertainty contributed strongly to the swift recovery. Although aggregate supply shocks and non-uncertainty-related aggregate demand shocks contributed to output and inflation dynamics throughout the pandemic and especially during the recovery, their contributions were quantitatively less important, at least for output dynamics. For inflation, the relative contributions of uncertainty shocks were particularly pronounced during the downturn, while aggregate demand shocks and, to a larger degree, aggregate supply shocks contributed substantially to the surge in prices that accompanied the recovery.

At a more general level, our results confirm that uncertainty shocks are an important driver of business cycle fluctuations and suggest that these shocks can even be the dominant source of changes in economic activity during specific periods. Moreover, while the adverse effects of higher uncertainty are typically emphasized, we show that reductions in uncertainty can be an important factor contributing to recoveries in economic activity as well.

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