Business Cycle Fluctuations: Financial Shocks versus Uncertainty Shocks*

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Abstract

What are the economic implications of financial and uncertainty shocks? By using a structural VAR, we show that financial shocks cause a decline in output and goods prices, while uncertainty shocks cause a decline in output and an increase in goods prices. In response to uncertainty shocks, firms increase their markups, in line with the theory of self-insurance against being stuck with too low a price. This explains why goods prices increase at the onset of a recession originated in financial markets. Financial and uncertainty shocks explain a large fraction of fluctuations in output and prices during the global financial crisis, while cost-push and demand forces prevail during the COVID-19 pandemic.

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I Introduction

While there is a large consensus arguing that output and goods prices decline after a financial shock, scientific evidence on the aggregate responses after an uncertainty shock is still inconclusive. On the one hand, an exogenous increase in bad uncertainty about the future can reduce irreversible investment, induce precautionary savings and lower consumption, or can rise unemployment due to search and matching frictions, such that uncertainty shocks reduce output and goods prices (Leland, 1968; Abel, 1983; Bernanke, 1983; Kimball, 1990; Bloom, 2009; Christiano et al., 2014; Leduc and Liu, 2016; Basu and Bundick, 2017). Similarly, good uncertainty associated to an expected increase in productivity can increase investment and economic activity (Hartman, 1972; Abel, 1983; Bar-ilan and Strange, 1996). On the other hand, if bad uncertainty exogenously increases, firms may increase their prices to self-insure against being stuck with too low a price should a recession not materialise; this increase in markups is contractionary (Born and Pfeifer, 2014; Fernández-Villaverde et al., 2015; Bonciani and van Roye, 2016; Fasani and Rossi, 2018).

We assess the business cycle response to financial and uncertainty shocks that are jointly identified using a Structural Vector Autoregression (SVAR) model for the United States (US) over the monthly period 1984-2019 and conclude that financial shocks cause a decline in output and goods prices, while uncertainty shocks cause a decline in output and increase in goods prices. This explains why goods prices tend to increase at the onset of three out of the four recessions since 1984, as they originated in financial markets with adverse shocks to the second moments prevailing (see Figures 1 and 2). This novel result in the empirical macroeconomic literature emerges irrespective of whether the employed uncertainty measure is obtained from surveys, financial variables or macroeconomic variables.

Financial and uncertainty shocks are identified along with demand shocks, interest rate shocks and cost-push shocks. This contrasts with the vast majority of the related literature, where some shocks in the system are left unidentified. Canova and Paustian (2011), however, suggest that inference can be improved upon by identifying other macroeconomic shocks even if they are not essential for the analysis. While supply shocks and interest rate shocks can be readily disentangled by using a very standard set of sign restrictions, the identification of demand, financial and uncertainty shocks is more challenging. These three shocks, that cannot be identified using standard sign restrictions, can be identified using the narrative restriction identification à la Antolín-Díaz and Rubio-Ramírez (2018). We introduce a modification of this identification scheme by incorporating that, at a given date, some of the unrestricted shocks are allowed to have a stronger contribution to the unforecastable change of the variable of interest if they shift the variable in the opposite direction compared to the contribution of the restricted shock. This feature allows the unrestricted shocks at that date (e.g., monetary policy) to counteract immediately the adverse effects of the restricted shocks (e.g., financial and uncertainty); a flexibility that is precluded in the original contribution of Antolín-Díaz and Rubio-Ramírez (2018).

We find that financial shocks generate a large contraction in output and goods prices and have larger effects than adverse demand shocks in the medium-term. The effects on output and prices are permanent in the presence of financial shocks. Uncertainty shocks also cause a decline in output, but goods prices tend to increase temporarily. In response to uncertainty shocks, we find that firms increase their markups, in line with the theory of self-insurance against being stuck with too low a price; but also that households tend to increase their savings rate given the uncertainty regarding future income. Together, these responses are contractionary with prevailing rising prices over the next two years. We also find that higher uncertainty during recessions is partly an endogenous response to demand and financial shocks.

It is important to emphasise that we do not impose any a priori sign restrictions to identify financial and uncertainty shocks. The results are uniquely driven by a minimal number of narrative restrictions: risk repricing in July 2007 identifies the financial shocks by providing the largest positive contribution to the dynamics of US corporate spreads; while 9/11 in 2001 and the liquidity crisis in August 2007 identify the uncertainty shocks by providing the largest positive contribution to the dynamics of the uncertainty gauge.

It is useful to define financial and uncertainty shocks. Financial shocks are characterised by an unexpected worsening of conditions in credit markets with tightness in business financing and repricing of risks, which we capture with the so-called Gilchrist-Zakrajšek (GZ) corporate credit spread, as suggested by Gilchrist et al. (2009), Gilchrist and Zakrajšek (2012), and corroborated by Caldara et al. (2016), Brunnermeier et al. (2021) and Caggiano et al. (2021). Uncertainty is the result of a rare unknown economic event, which makes the economic outlook less predictable. Uncertainty is also asymmetric with good uncertainty predicting an increase in economic activity and bad uncertainty forecasting a decline in output (Segal et al., 2015). We employ six main alternative uncertainty gauges suggested by the literature: (1) consumers' perceived uncertainty by Leduc and Liu (2016), (2) the US Composite Indicator of Systemic Stress (CISS) by Kremer et al. (2012), (3) the stock market volatility by Bloom (2009), (4) the economic policy uncertainty (EPU) by Baker et al. (2016), (5) macroeconomic uncertainty by Jurado et al. (2015, JLN) and financial uncertainty by Ludvigson et al. (2020, LMN). The first four gauges are characterised by both features: unpredictability and asymmetry. The last two gauges are characterised by unpredictability and treat the state of the economy symmetrically with higher values due to increases in either good or bad uncertainty.[1]

As for the method, Brunnermeier et al. (2021) investigate the role of credit aggregates and credit conditions using a SVAR with shocks identified by heteroskedasticity, where changes in the volatility of the VAR innovations are postulated together with the assumption that the transmission mechanisms of the shocks (i.e. estimated coefficients and impact matrix) remain invariant. They show that financial shocks reduce output and goods prices. This approach has one important limitation for our purpose: the economic interpretation of shocks can only be provided ex-post, making the distinction between demand, financial and uncertainty shocks, which is the focus of our study, a difficult task. The key issue is that these three

[1] This symmetry applies also to Scotti (2016).

drivers may be consistent with the same empirical evidence.

One strand of the literature identifies two shocks. Caldara et al. (2016) identify both financial and uncertainty shocks maximizing the largest responses in selected measures over the first six months, but the strategy requires a recursive assumption and the results depend on the ordering of the optimization problem. In a similar fashion, Cascaldi-Garcia and Galvao (2021) identify uncertainty shocks and total factor productivity shocks. Furlanetto et al. (2019) identify both financial and uncertainty shocks imposing restrictions on the ratio of the IRFs of credit spreads and the VIX, and traditional sign restrictions on impact for output and prices, including however the same sign response on goods prices, regardless of the shock-type. Caggiano et al. (2021) use the Furlanetto et al. (2019)'s identification assumption, leaving unrestricted the responses of output and goods prices; additionally, they impose narrative restrictions, such that in the same period stock market volatility is primarily driven by uncertainty shocks and credit spreads are primarily driven by financial shocks. The impact on goods prices is uncertain. Alessandri and Mumtaz (2019) orthogonalise the uncertainty shocks against a financing condition index, but this requires to deal with a recursive representation of the economic system; while Brianti (2021) uses data on corporate cash balances to disentangle the two shocks.

Another strand of the literature disregards financial shocks and focuses the analysis on disentangling the economic responses of financial uncertainty shocks and macroeconomic uncertainty shocks (Ludvigson et al., 2020; Carriero et al., 2018a,b).

Finally, an extensive empirical literature identifies only financial shocks or uncertainty shocks by using (i) the Cholesky recursive method (Bloom, 2009; Gilchrist and Zakrajšek, 2012; Bachmann et al., 2013; Caggiano et al., 2014; Jurado et al., 2015; Rossi and Sekhposyan, 2015; Segal et al., 2015; Baker et al., 2016; Leduc and Liu, 2016; Scotti, 2016; Rossi et al., 2018; Chavleishvili and Manganelli, 2019; Altig et al., 2020; Haque and Magnusson, 2021; Ferrer et al., 2021), (ii) the instrumental variable method (Stock and Watson, 2012), (iii) a statistical approach that maximizes the contribution of the shock of interest to the forecast error variance decomposition (FEVD) of a selected variable (Kwon, 2020), (iv) sign restrictions (Larsen, 2021), or (v) heteroscedasticity of the shocks (Ferrer et al., 2021). However, as pointed out by Stock and Watson (2012), financial shocks and uncertainty shocks estimated separately might be highly correlated; thereby, distinct financial and uncertainty shocks are not identified.

The remaining of the paper is structured as follows. Sections II and III describe the identification of the shocks and the dataset. Section IV discusses the results. Section V quantifies the importance of shocks in specific periods. Section VI provides a discussion associated to other methods. Section VII concludes.

II Framework and identification

II.A SVAR setup

An SVAR can be written as:

$$A_0 y_t = A_1 y_{t-1} + A_2 y_{t-2} + ... + A_K y_{t-K} + \varepsilon_t, \tag{1}$$

where y_t is the $N \times 1$ vector of endogenous variables (real GDP, GDP deflator, the 10-year Treasury yield, the GZ corporate bond spreads and one at a time the uncertainty measures reported in Figure 2), K is a finite number of lags, ε_t is the column vector of structural shocks, A_0 describes the contemporaneous relations between the variables, while matrices A_k, $k \in [1, 2, \ldots, K]$, describe the dynamic relationships. The structural shocks are assumed to be independent of each other with variance normalised and equal to unity.

The system (1) implies a structural moving average representation: $y_t = R(L)\varepsilon_t$, where $R(L)$ is a polynomial in the lag operator. The system in (1) is estimated in its reduced form:

$$y_t = A_1^* y_{t-1} + A_2^* y_{t-2} + ... + A_P^* y_{t-K} + u_t, \tag{2}$$

where the reduced form residuals $u_t = A_0^{-1}\varepsilon_t$ and where $A_k^* = A_0^{-1}A_k$.

The moving average representation of (2) is $y_t = C(L)u_t$. Therefore, the reduced form response function, $C(L)$, is related to the structural impulse response function by $R(L) = C(L)A_0^{-1}$. To identify the structural shocks and obtain the structural impulse responses, $S = A_0^{-1}$ ought to be identified, such that $\Sigma_u = SS'$, where Σ_u is the variance-covariance matrix of the reduced form errors. The decomposition $\Sigma_u = SS'$ is not unique. For any H such that $HH' = I$, the matrix SH also satisfies this condition: $SH(SH)' = SHH'S' = SS' = \Sigma_u$. Therefore, starting from any arbitrary $\tilde{S}$, such that $\Sigma_u = \tilde{S}\tilde{S}'$, alternative decompositions can be found by post-multiplying by any H. The entire set of permissible impact matrices is infinite and the impact matrix cannot be identified uniquely from the data.

II.B Identification: Signed contribution restrictions

Prior assumptions are required to achieve identification. The sign restrictions on the impact matrix, A_0^{-1}, are unable to deliver identification of the structural shocks in our system. Therefore, we complement our set of impact sign restrictions with narrative restrictions in the spirit of Antolín-Díaz and Rubio-Ramírez (2018), but with a variation such that the assumptions are less restrictive.

Sign narrative restrictions. As in Antolín-Díaz and Rubio-Ramírez (2018), the narrative restriction based exclusively on the sign of the shocks implies that the value of the identified structural shock i on a specific date t is positive or negative:

$$\varepsilon_{i,t} > 0 \textit{ or } \varepsilon_{i,t} < 0 \textit{ at a given } t. \tag{3}$$

For example, suppose that there is substantial evidence to assume that the economy was hit by an uncertainty shock in a given period, e.g. in September 2001 after the terrorist attacks. Then, we can select and save the draws if $\varepsilon_{uncertainty,t} > 0$ in September 2001.

Signed contribution restrictions. Typically, as a consequence of adverse shocks, policymakers intervene providing macroeconomic support. Particularly the monetary policymaker can provide liquidity to the financial markets in abundance and immediately, such that the policy becomes expansionary offsetting the implications of the adverse shock. Therefore, differently from Antolín-Díaz and Rubio-Ramírez (2018), we allow other shocks in the same period to have a larger contribution in absolute value, if they shift the variable in the opposite direction. The signed contribution restriction implies that the value of the column vector of $\varepsilon_{i,t}$ at date t is such that the selected shock can explain the largest fraction of the unexpected fluctuation of a specified variable in the column data vector y_t among the shocks that in the selected period have the same sign as the shock of interest.[2]

Formally, let $h_{i,t}$ denote the contribution of the shock of interest to the variable of interest i at time t; let $H_{i,t}$ denote the $(n-1)\times 1$ vector that collects the contributions of the other shocks in the VAR to the same variable of interest on the same date; and let $\mathbb{S}(H_{i,t}, B_{i,t})$ denote the vector-valued function that selects the elements from $H_{i,t}$ for which the corresponding element in the same-sized vector $B_{i,t}$ equals one, where $B_{i,t} = \mathbb{1}((H_{i,t} \cdot sign(h_{i,t})) > 0)$ is a vector-valued indicator function. For a specific date t, we impose:

$$h_{i,t} > max\left(\mathbb{S}(H_{i,t}, B_{it})\right). \tag{4}$$

The traditional approach by Antolín-Díaz and Rubio-Ramírez (2018) assumes that the draw is accepted if the contribution of the identified shock to the unexpected variation in the variable of interest is the largest in absolute value at time t, i.e., $|h_{i,t}| > max(|H_{i,t}|)$. Instead, we allow other shocks to have a stronger contribution, if they have the opposite sign. For example, let the number of variables be $n = 5$ and suppose that we are interested in the effect of each of the five structural shocks on the uncertainty variable, which is the fifth variable of the VAR system. In that case, we compute the following at a given t:

$$y_{5t} - E_{t-1}[y_{5t}] = a_{51}\varepsilon_t^{supply} + a_{52}\varepsilon_t^{interestrate} + a_{53}\varepsilon_t^{demand} + a_{54}\varepsilon_t^{financial} + a_{55}\varepsilon_t^{uncertainty},$$

[2]It is important to emphasise that the standard historical decomposition of shocks depends on shocks at date t as well as the infinite history of structural shocks. In the identification with narrative restriction, only the relative importance of the shocks at date t is used.

where a_{ij} are the elements of the impact matrix S and $E_{t-1}[y_{5t}]$ is the expectation of y_{5t} at $t-1$ estimated within the VAR system. In the terrorist attacks case, the draw is accepted if $\varepsilon_{uncertainty,t}$ is positive in September 2001 and $a_{55}\varepsilon_{uncertainty,t}/(y_{5t} - E_{t-1}[y_{5t}])$ has the largest value compared to the contribution of all other individual shocks with the same positive sign. Similarly, if the episode of interest is a decline in the interest rate (being the third variable in the system), the draw is accepted if $\varepsilon_{interestrate,t} < 0$ and $a_{33}\varepsilon_{interestrate,t}/(y_{3t} - E_{t-1}[y_{3t}])$ has the lowest value compared to the contribution of all other individual shocks with the same negative sign.

II.C Episodes of history

It is generally accepted that adverse demand shocks cause a fall in output and goods prices, a widening of credit spreads, because risk premia are counter-cyclical, an increase in uncertainty, because the economic outlook becomes less predictable and a fall in long-term interest rates, as economic agents expect the monetary policymaker to support the economy. This theory underlies the identification of demand shocks as described in Table 1. As for the financial and uncertainty shocks, we make use of exceptional developments in specific periods to identify them (e.g. extraordinary large shocks), such that they are orthogonal vis-à-vis all other shocks in the system. The event chosen are highlighted in Figure 3.

Financial shocks. Given that financial shocks capture tightness in business financing conditions, the repricing of risks in July 2007 is used to identify the financial shocks by providing the largest positive contribution to the dynamics of US corporate spreads in this specific month. In July 2007, the rating agencies announced a mass downgrade of products that were backed by sub-prime mortgages. S&P and Moody's downgraded assets with an original value of USD 7.3 and 5.2 billion, respectively. These decisions surprised economic agents and credit spreads rose on average by 70 basis points relative to the previous month (see Panel F), as risk was repriced, while uncertainty about the economic outlook declined in the case of consumers' uncertainty and EPU (see Panels I and R, although they refer to

August 2007, the previous month is also visible), remained broadly invariant as in the case of the CISS (see Panels L) and marginally increased as in the case of VXO, financial and macroeconomic uncertainties (see Panels O, U and X). The mass downgrade was seen as an ad-hoc intervention and ratings were expected to remain stable thereafter.[3]

Uncertainty shocks. To identify the uncertainty shocks we use two key events: (i) the 9/11 terrorist attacks in 2001, which increased consumers' uncertainty, the CISS and EPU by about three times as much relative to the previous month (Panels H, K, Q), the VXO by half (Panel N) and the financial and macroeconomic uncertainties by about 10% (Panels T and W), and (ii) the inter-bank liquidity crisis in August 2007, which increased fourfold consumers' uncertainty and the CISS relative to the previous month (Panels I and L), three times as much EPU (Panel R), by half the VXO (Panel O) and by a smaller fraction the financial and the macroeconomic uncertainties (Panels U and X).

Supporting our choice, the Federal Open Markets Committee (FOMC) discussed the negative impact of uncertainty after 9/11 and Bloom (2009) used this event as a key uncertainty shock. In August 2007, the interbank market that provides liquidity to banks around the globe frozen completely, largely due to fear of the unknown (e.g. Ashcraft et al., 2011; Acharya and Merrouche, 2013), while credit spreads rose only marginally. Similarly, the FOMC declared on August 17 that financial market conditions had deteriorated and that tighter credit conditions and increased uncertainty had the potential to restrain economic growth going forward. In the September 18, 2007 meeting, the Committee refrained from providing an explicit assessment of the balance of risks, given the heightened uncertainty. Overall, 9/11 terrorist attacks and the inter-bank liquidity crisis generated panic and, therefore, they are well suited to identify uncertainty shocks, by assuming that they provide the largest positive contribution to the dynamics of uncertainty indicators.

[3]On the 20th July of 2007, Moody's described structured investment vehicles (SIVs) – off-balance sheet vehicles which had been used to finance the purchase of mortgage-backed securities – as an "oasis of calm in the sub-prime maelstrom" (see `https://fcic-static.law.stanford.edu/cdn_media/fcic-docs/2007-07-20%20SIVs%20-%20An%20Oasis%20of%20Calm%20in%20the%20Sub-prime%20Maelstrom%20(Moody's%20Special%20Report).pdf`).

Finally, we use the period around the Lehman Brothers' bankruptcy to restrict the sign of both financial shocks and uncertainty shocks, assuming that both shocks are positive in September and October 2008. After the bankruptcy of Lehman on September 15, 2008, the GZ corporate credit spreads (Gilchrist and Zakrajšek, 2012) rose by 100 basis points in September and 370 basis points in October (Panel G). At the same time in September 2008, credit tightened as reported by the survey among senior loan officers of banks (Senior Loan Officer Opinion Survey on Bank Lending Practices) conducted by the Federal Reserve Board. Banks began holding more capital and becoming risk-averse in granting loans and firms were less able to borrow as much as before, as shown by Jermann and Quadrini (2012).

Also Bernanke (2009), in his reflections one year after Lehman's bankruptcy, pointed out that the financial shocks of September and October 2008 severely damaged the global economy. In the same spirit, Ivashina and Scharfstein (2010) document a sharp fall in credit supply soon after the Lehman collapse. At the same time, there is no doubt that uncertainty about the economic outlook rose sharply after Lehman's bankruptcy (e.g. Ludvigson et al., 2020), and this is associated to the uncertainty about the value of new financial products, such as the securitization of mortgages and other debt obligations, as well as the implications of credit default swaps contracts and the fact that banks used customer deposits to invest in swaps. Also Caggiano et al. (2021) select these two months to identify the financial and the uncertainty shocks. The consumers' uncertainty gauge, CISS, VXO and EPU rose by two or three times over these two months (Panels J, M, P and S), while the financial and macroeconomic uncertainty measures increased by about 20% (Panels V and Y).

Demand shocks. We identify also a narrative event for demand shocks and show two sets of results: one where this narrative is imposed and one where it is not. The narrative restriction assumes that demand shocks increased GDP in January 2006 (Panel A). Real US GDP grew at an annual rate of 5.3% in the first quarter of 2006 and was much larger than the 2.5% increase registered in the fourth quarter of 2005 and even stronger than the FOMC's expectation in the March 2006 Greenbook. Most of the growth came from consumer

Table 1: Sign and narrative restrictions

	Supply	**Interest rate**	**Demand**	**Financial**	**Uncertainty**
Variables			*Sign restrictions on the impact matrix*		
Real GDP	+		-		
Goods prices	-	-	-		
Interest rate		+	-		
GZ credit spreads		+	+	+	
Uncertainty			+		+
YY / MM			*Sign narrative restrictions and signed contribution restrictions*		
94/02		Interest rate $\uparrow\uparrow$			
09/03, 13/09		Interest rate $\downarrow\downarrow$			
06/01			GDP $\uparrow\uparrow$		
07/07				Credit spreads $\uparrow\uparrow$	
01/09, 07/08					Uncertainty $\uparrow\uparrow$
YY / MM			*Sign narrative restrictions only*		
08/09, 08/10				Credit spreads $\uparrow$	Uncertainty $\uparrow$

spending, which surprised on the upside. The FOMC wrote that "*About half of our miss in the first quarter reflected higher-than-expected federal spending..... Household and business investment, too, have come in above our expectations, and we read domestic demand as having somewhat greater momentum that we had earlier thought*". Given that real retail sales grew at an annual rate of 26.9% in January 2006 and consumer price index (CPI) and producer price index (PPI) rose by about an annualised 7% in the same month with upward implications for the GDP deflator (Panel B), we assume that most of the GDP increase in this month is due to a favourable demand shock.

Interest rate shocks. We impose the narrative information on interest rates to capture the adverse effect on economic activity of an exogenous increase in the risk free rate. Monetary policy is certainly affecting the Treasury curve and this is particularly the case after the Federal Fund rate reached the lower bound and quantitative easing was introduced in 2009. Our study begins from 1984 in order to take into account the change in volatility of variables since then. Therefore, we use February 1994 to identify a fall in interest rates due to a contractionary monetary policy shock, which Antolín-Díaz and Rubio-Ramírez (2018) classify as of particular interest because medium to longer-term Treasury rates rose by about 60 basis points (Panel C), but output accelerated during 1994. Therefore, this decision was not shaped by a forthcoming recession.

We then use as additional narratives the expansionary monetary policy decisions in March 2009 (Panel D) and September 2013 (Panel E). Swanson (2020) shows that the "QE1" announcement for the "large-scale asset purchases" (LSAPs) at the zero lower bound generated an extraordinary shock on March 18, 2009, on the long-term interest rates, as the announcement was a major surprise to financial markets. In our monthly dataset, the long-term interest rates declined by 55 basis points in March 2009 relative to the previous month. The middle of 2013 corresponds to the "taper tantrum" in financial markets. In May 2013, the Federal Reserve Chair Ben Bernanke announced that the FED would, at some future date, reduce the volume of its bond purchases. This prospective policy of reducing the rate of FED asset purchases changed investor expectations, who responded immediately by selling bonds and increasing the long-term interest rates by 50 basis points in the same month. Subsequently, the FOMC released a hawkish growth forecast for the economy in June 2013, signalling that a tapering was imminent, and interest rates rose further by 40 basis points in June and thereafter during the summer. Overall, between May and August 2013, the long-term interest rates rose by a cumulative 120 basis points. It is debatable if the FED communication was a commensurate endogenous response to the positive macroeconomic developments or a tightening response to an overheated economy. In September 2013, the FOMC surprised the markets by not tapering and long-term interest rates declined by 15 basis points in that month. Swanson (2020) quantifies this latter decision as the second largest LSAP shock and we use the September 2013 developments in interest rates as part of the narrative restriction set.

The identification of the interest rate shock is complemented with sign restrictions on the contemporaneous impact matrix: we assume that goods prices decline, as in Uhlig (2005) and Antolín-Díaz and Rubio-Ramírez (2018), that corporate spreads widen in line with the findings of Caldara and Herbst (2019), Jarociński and Karadi (2020) and Brunnermeier et al. (2021) and leave the response of output unrestricted.

Cost-push shocks. Finally, cost-push shocks are included by simply assuming that real activity and good prices respond moving in opposite directions, in contrast with demand shocks which shift these variables in the same direction. The full set of sign and narrative restrictions summarised in Table 1 allows for the joint identification of the five shocks.

III Dataset

The analysis is performed using monthly data over the period from January 1984 to November 2019 in order to take into account potentially important structural changes in the transmission of shocks (e.g. Giannone et al., 2008; Canova, 2009; Gambetti and Galí, 2009; Del Negro et al., 2020), or in the monetary policy rule (e.g. Clarida et al., 2000; Lubik and Schorfheide, 2004; Boivin and Giannoni, 2006; Benati and Surico, 2009) which might have occurred in the mid-1980s, as a result of the "Great Moderation". The end of the sample is justified by dropping the extreme volatile observations associated to COVID-19, which started in China in December 2019.

The VAR uses real GDP, GDP deflator, the 10-year Treasury yield, the GZ corporate bond spreads and one of the uncertainty measures.[4] Real GDP and GDP deflator are interpolated, as often carried out in the literature (Bernanke and Mihov, 1998; Uhlig, 2005; Antolín-Díaz and Rubio-Ramírez, 2018). GDP has been interpolated using industrial production and real retail sales. GDP deflator has been interpolated using the consumer price index and the producer price index.[5]

We use the long-term Treasury rate, which together with corporate spreads control for financing conditions. Treasury rates are highly affected by monetary policy also because monetary policy communication has been conducted by implicit (before reaching the lower bound) or explicit (thereafter) forward guidance and quantitative easing.

[4]The VAR uses 12 lags and a constant and employs variables in level with real GDP and GDP deflator in logs. The model is estimated using standard Bayesian methods with a flat prior.

[5]The monthly interpolation is carried out using the method suggested by Chow and Lin (1971).

III.A Corporate bond spreads to identify financial shocks

Corporate bond spreads are used in the literature to identify financial shocks: increases in corporate bond spreads are associated with a worsening of credit conditions, with tightness in business financing and with the repricing of risks. They are well captured by the so-called GZ corporate credit spreads (Gilchrist et al., 2009; Gilchrist and Zakrajšek, 2012; Brunnermeier et al., 2021), which are duration adjusted security-specific credit spreads constructed using individual security level data. We compile the series using the individual bond data, which form the constituencies of ICE Bank of America (BofAML) US Corporate Indices, issued by US nonfinancial corporations.[6]

Specifically, for each security j, we construct credit spread $s_{j,t}[k]$ by subtracting from the yield to maturity, $R_{j,t}[k]$, the Treasury yield of a similar duration k, $i_t[k]$,[7] $s_{j,t}[k] = R_{j,t}[k] - i_t[k]$ and the corporate bond spread index is a simple average: $\overline{s}_t[k] = \frac{1}{N_t} \sum_j \left(s_{j,t}[k] \right)$, where N_t is the number of bonds at time t.

The BofAML database is available since January 1997. Corporate bond spreads for previous years are chained back using the index provided by Gilchrist and Zakrajšek (2012).[8]

The measure of the tightness of financial market conditions is reported in Figure 1. It shows the compensation demanded by bond investors for bearing exposure to US nonfinancial corporate credit risk. It is counter-cyclical and rises sharply during NBER recessions, with the exception of the 1990–1991 recession.

[6] The outstanding amount of corporate bonds in the BofAML database issued in US dollars is about 9 trillions of which 6 trillion issued in the US. The data cover investment grade and high yield corporate debt publicly issued in the major markets. Qualifying securities must satisfy the following requirements to be included: (i) a minimum size requirement of US dollar (USD) 250 million, (ii) a rating issued by Moody's, S&P or Fitch, (iii) a fixed coupon schedule, and (iv) a minimum 18 month maturity at issuance. We retain bonds with a residual maturity above 11 months that are available for at least two consecutive months.

[7] The Treasury yield curve is provided by the FED (`https://www.federalreserve.gov/data/yield-curve-tables/feds200628_1.html`) and is constructed using the method by Gürkaynak et al. (2007).

[8] GZ corporate spreads are available from the authors website only up to August 2016. The correlation of the two series over the overlapping period between January 1997 and August 2016 is 97.9% in levels and 92.1% in first difference.

III.B Alternative gauges to identify uncertainty shocks

Uncertainty is the result of a rare unknown negative economic event, which makes the economic outlook less predictable. It is asymmetric with higher good uncertainty predicting an increase in economic activity and higher bad uncertainty forecasting a decline in output (Segal et al., 2015).

The large number of measures used in the literature to identify an uncertainty shock suggests that there is little consensus on a preferred measure. Some authors use asset prices, such as the stock market volatility (Bloom, 2009; Bekaert and Hoerova, 2014; Caldara et al., 2016; Cascaldi-Garcia and Galvao, 2021; Haque and Magnusson, 2021) or the CISS (Chavleishvili and Manganelli, 2019), others use news-based indices (Baker et al., 2016; Larsen, 2021; Altig et al., 2020; Cascaldi-Garcia and Galvao, 2021), the conditional variance of forecast errors (Jurado et al., 2015; Rossi and Sekhposyan, 2015; Segal et al., 2015; Scotti, 2016; Rossi et al., 2018; Caldara and Herbst, 2019; Ludvigson et al., 2020; Cascaldi-Garcia and Galvao, 2021),[9] or surveys (Leduc and Liu, 2016).[10]

We employ the following six alternative measures: one based on survey data, one based on news, one based on macroeconomic data, and three based on financial market data. Four of these measures rise with bad uncertainty and decline with good uncertainty, while two of them rise with both good and bad uncertainty. All these uncertainty measures tend to increase at the onset of recessions (see Figure 2).

[9] Mumtaz and Theodoridis (2018) and Alessandri and Mumtaz (2019) estimate of a measure of uncertainty that encompasses volatility from the real and financial sectors of the economy, which resembles Jurado et al. (2015)'s measure.

[10] Some papers have used the cross-sectional dispersion of macro forecasts (Bachmann et al., 2013; Caldara et al., 2016; Altig et al., 2020; Cascaldi-Garcia and Galvao, 2021), or the cross-sectional dispersion of firms' sales or productivity (Bloom, 2009; Bloom et al., 2018). However, measures of cross-sectional dispersion of macroeconomic forecasts are not necessarily associated with a rise in economic uncertainty. Disagreement in survey forecasts can increase, if forecasters have a different view of the world (Jurado et al., 2015).

III.B.1 Consumers' perceived expectations

The uncertainty measure, based on the Michigan consumer sentiment survey suggested by Leduc and Liu (2016), is rising with negative economic events. A higher index implies higher bad uncertainty about the economic outlook. Its correlation with other uncertainty measures is positive, but relatively small: the correlation over the 1984-2019 sample period is 42.9% with CISS, 20.6% with VXO, 20.8% with EPU, 28.4% with macroeconomic uncertainty and 20.8% with financial uncertainty.

The Michigan consumer sentiment survey analyses the "Reasons for opinions for buying conditions for vehicles". The following questions are asked:

1. "*Speaking now of the automobile market, do you think the next 12 months or so will be a good time or a bad time to buy a new vehicle, such as a car, pickup, van or sport utility vehicle?*"

2. "*Why do you say so?*"

Multiple answers are allowed, covering a range of economic reasons in good and bad times associated to demand, supply, financing conditions and uncertainty:

- price dynamics (Good Time / Prices low; Good Time / Prices will increase; Bad Time / Prices high),

- interest rate developments (Good Time / Interest rates low; Good Time / Rising interest rates; Bad Time / Interest rates high),

- quality of the vehicles (Good Time / Fuel efficiency; Bad Time / Poor selection),

- ability to afford it after the purchase (Good Time / Times good; Bad Time / Can't afford; Bad Time / Gas prices);

- uncertainty (Bad Time / Uncertain future).

The uncertainty measure we use is the fraction of respondents reporting that indicate that it is a bad time to purchase a vehicle, because the future is uncertain.[11] It rises sharply during NBER recessions (see Panel A of Figure 2) and it is positively correlated with corporate spreads (44.9% over the sample period 1984-2019), although it is not explicitly based on financial market data. Risk and uncertainty are correlated because shocks to second moments (uncertainty) do affect risk and vice versa (Bloom, 2009; Bekaert and Hoerova, 2014). This highlights the need to incorporate the interactions between credit conditions and uncertainty in the analysis.

III.B.2 CISS, VXO and EPU

CISS, VXO and EPU share with the consumers' uncertainty gauge the asymmetric signal, in the sense that a low (high) value implies low (high) bad uncertainty.

The US CISS is an aggregation of 15 indicators capturing financial stress symptoms. It is measured using indicators from money markets, bond markets, equity markets, and foreign exchange markets (Kremer et al., 2012). Over the sample period 1984-2019, it is positively correlated with the VXO (77.7%) and with the aforementioned consumers' uncertainty gauge (42.9%).

The Baker et al. (2016)'s EPU is policy-related economic uncertainty measure, constructed by aggregating information from three types of underlying components: i) the newspaper coverage of policy-related economic uncertainty; ii) the number of federal tax code provisions set to expire in future years; and iii) the disagreement among economic forecasters. It is also positively correlated with consumers' uncertainty and the US CISS (52.5% and 33.4% over the sample period 1984-2019, respectively).[12]

[11] The series are weighted by age, income, region, and sex, and is nationally representative. The relevant data are available on the Michigan Survey of Consumers website (https://data.sca.isr.umich.edu/data-archive/mine.php, Table 38, Reasons for Opinions for Buying Conditions for Vehicles, in the column "Bad Time / Uncertain Future".

[12] The EPU is available from January 1985. To complete the series, the values for 1984 are chained with the US historical news-based policy index, also available from the same authors.

III.B.3 Macroeconomic and financial uncertainty

We cross-check the results using JLN' macroeconomic uncertainty and LMN' financial uncertainty. They are both symmetric measures in the sense that high uncertainty can correlate with either rising or decreasing output. The two measures are only weakly positively correlated with consumers' uncertainty (28.4% and 20.8% over the sample period 1984-2019, respectively), but highly positively correlated with CISS (70.7% and 67.0% over the same sample period, respectively),

IV Response with signed narrative restrictions

We start our analysis with the recursive identification approach often used in the literature with the uncertainty gauge being ordered either first or last in the VAR setup. We replicate recurring results documented in the literature; that is, an uncertainty shock sharply reduces output, particularly if the uncertainty measure is ordered first (e.g. Bloom, 2009; Bachmann and Bayer, 2013; Caggiano et al., 2014; Jurado et al., 2015; Rossi and Sekhposyan, 2015; Baker et al., 2016; Leduc and Liu, 2016; Scotti, 2016; Rossi et al., 2018; Altig et al., 2020). The results on goods prices depend on the type of uncertainty measure used, the order of the variables and the inclusion or exclusion of GZ corporate spreads in the VAR specification (see Appendix).

Then, we estimate the model identifying only two shocks, the financial and the uncertainty shocks, using the restrictions described in Table 1. The results, displayed in Figure 4, suggest that output and goods prices decline in response to a financial shock, while output contracts and goods prices are unresponsive after an uncertainty shock (i.e. the 68% credible set includes zero), as in Caggiano et al. (2021). Even though such a partially identified VAR where some shocks are left unidentified is a standard tool in empirical macroeconomics, it may entail an important drawback. More precisely, as shown by Canova and Paustian (2011), inference related to the shocks of interest may be improved by identifiying additional macroeconomic shocks, even though they are not of primary interest for the analysis.

Therefore, we show the importance of identifying financial and uncertainty shocks along with other standard macroeconomic shocks such as demand, supply and interest rate shocks. We estimate the model identifying five shocks jointly using the restrictions described in Table 1. If we impose only sign restrictions, it is impossible to assign an economic interpretation to all shocks and the reduced form covariance restrictions alone produce inconclusive results (see Appendix). The VAR with five shocks is identified when adding the narrative restrictions.

IV.A IRFs using consumers' perceived uncertainty

Impulse response functions (IRFs) are selected by incorporating into the model external knowledge about the sign and the size of the shocks in a small number of key historical episodes and, therefore, shocks are labelled ex-ante. They are shown in Figure 5. The first panel provides the impact of the cost-push shocks, the second panel the impact of the interest rate shocks, the third panel the impact of demand shocks, the fourth panel the impact of financial shocks and the fifth panel the impact of uncertainty shocks. Each plot provides two sets of IRFs, one in which a narrative is also imposed on demand shocks and one where this additional restriction is not imposed.

The results suggest that the response to financial shocks is similar to the response to demand shocks as far as the sign of the variables is concerned. They decrease output, goods prices and interest rates, and increase corporate spreads and uncertainty. Differences emerge with regard to the size and the persistence. Financial shocks generate a larger contraction in output and in the long run on goods prices. At the same time, the impact on interest rates and uncertainty is smaller. The effects on output and goods prices are permanent in the presence of financial shocks. In response to uncertainty shocks, the permanent negative response of output is larger than financial shocks. In contrast, goods prices increase for about two years.

The results suggest that interest rate conditions are an important part of the mechanism through which financial and uncertainty shocks affect the macroeconomy. After financial shocks, the decline in interest rates attenuate the negative impact on output and inflation. Conversely, in response to uncertainty shocks, interest rates tend to increase following the increase in goods prices; as a result, the fall in output is larger.

Consistently with conventional wisdom, financial shocks increase uncertainty, but with a lag, while uncertainty shocks raise corporate spreads immediately. Contrary to the findings by Caldara et al. (2016), the uncertainty shocks identified in our framework do lead to a deterioration in financing conditions. These positive spillovers between corporate spreads and uncertainty amplify significantly the effects of financial and uncertainty shocks.

It is also worth mentioning that after negative supply shocks (i.e. higher production costs), the 10-year interest rate is muted in the very short-term and tends to increase only after six months; conversely, corporate spreads and uncertainty are marginally affected and tend to decline, whereas they all increase immediately in response to uncertainty shocks. The different implications on interest rates, corporate spreads and uncertainty, whose response is immediate and on the rise in the presence of uncertainty shocks, distinguish the latter shocks from supply shocks.

The results are broadly independent whether imposing the additional narrative restriction to identity the demand shocks. The only variable that is affected is GDP in response to demand shocks and prices in response to uncertainty shocks, as the narrative sharpens the econometric results narrowing the bands to evaluate statistical significance.

IV.B IRFs using other uncertainty measures

To check the robustness of our results, we substitute the consumers' perceived uncertainty gauge with one of the other five alternative uncertainty measures. Even though these measures are constructed using completely different approaches, the results confirm the aforementioned findings that financial shocks redeuce output and goods prices, while uncertainty shocks reduce output and increase goods prices (see Figures 6-7). The response of all variables to the other three identified shocks is very similar with complete results provided in the Appendix.

When using either CISS or EPU, the impact of uncertainty shocks on output is somewhat smaller than previously recorded, while the positive impact on goods prices is more long lasting. When using VXO, the impact of uncertainty shocks on output is one third than that estimated using consumers' perceived uncertainty, while the positive impact on goods prices is about half, but the 68% credible set includes zero.

Similar conclusions can be drawn if we proxy uncertainty with LMN' financial uncertainty. The response of the variables to an uncertainty shock is very similar to those obtained using consumers' perceived uncertainty. The impact on goods prices is much less persistent if employing JLN' macroeconomic uncertainty; but the key results that an uncertainty shocks reduced output and raise goods prices remain valid.

The results also confirm that uncertainty shocks bring about an increase in corporate spreads immediately regardless of the uncertainty gauge used, while financial shocks increase uncertainty with a lag and reduce output and prices permanently, regardless of the asymmetric uncertainty measure used. The results are also broadly independent whether imposing the additional narrative restriction to identity the demand shocks. Conversely, when using LMN' financial uncertainty and JLN' macroeconomic uncertainty, financial shocks tend to have no impact on goods prices and a negative impact on uncertainty. The symmetric nature of the index might be behind these results.

Similar conclusions can also be drawn if we exclude the GZ credit spreads from the model and financial shocks are not identified individually. Also in this case, uncertainty shocks decrease output and increase goods prices, regardless of the measure used to identify them (see Figure 8). Yet, controlling for GZ credit spreads and financial shocks makes the median impact of uncertainty shocks on output using EPU more negative with the correspondent 68% credible sets all in negative territory and on goods prices using CISS or VXO more positive with the correspondent 68% credible sets all in positive territory for about three years. Instead when using consumers' perceived uncertainty, the response of variables to the identified uncertainty shocks are very similar whether or not including GZ credit spreads in the VAR specification. This suggests that consumers' perceived uncertainty is less affected by shifts in risk attitudes and, therefore, is a more reliable uncertainty indicator about the economic outlook. It is useful to point out that the survey's respondents can disentangle risk and uncertainty in their responses, because several multiple answers are provided covering a range of economic reasons in good and bad times associated to risk and uncertainty

IV.C Response of price markups and savings rate to uncertainty shocks

The results discussed above are consistent with models featuring the presence of frictions in financial markets. Both financial shocks and uncertainty shocks imply a tightening in financial conditions and a contraction in credit supply available to businesses and households, and cause a decline in spending and production. Yet, the results suggest that financial shocks decrease goods prices, while uncertainty shocks increase them. Such a positive response of goods prices to uncertainty shocks is not new in the New Keynesian Dynamic Stochastic General Equilibriun literature (e.g. Born and Pfeifer, 2014; Fernández-Villaverde et al., 2015; Bonciani and van Roye, 2016; Fasani and Rossi, 2018), where firms tend to increase their markups in response to uncertainty shocks in order to avoid being stuck with too low a price should a recession not materialise.

To empirically evaluate this mechanism, we estimate how the two most preferred markup measures suggested by Nekarda and Ramey (2020) respond to our identified shocks. In particular, we estimate their reponse by local projections as described in equation (5), where y_t^j is either one of the two preferred quarterly markup measures, ϵ_t^i is the quarterly average of either the financial shock or the uncertainty shock identified in our SVAR, and the lag length is set to $p = 4$:

$$y^j_{t+h} = c^j_h + \beta^{i,j}_h \epsilon^i_t + \sum_{l=1}^{p} \gamma^i_{h,l} y^i_{t-l} + u^j_{t+h}. \tag{5}$$

The coefficients $\beta^{i,j}_h$ trace out the dynamic response of markup series j to shock i over horizons $h = 0, \ldots, 20$ quarters. The associated error bands are constructed in order to cover both the uncertainty around the estimated shock series and the estimation uncertainty around the local projection coefficients.

The results, displayed by the shaded area in Figure 9, suggest that price markups tend to increase for about three years after an exogenous increase in uncertainty, corroborating the aforementioned theory. In contrast, there is no clear response of the same markup measures after financial shocks (see red dotted lines). This observation can rationalize why goods prices tend to increase at the onset of a recession originated in financial markets.

Similarly, we can use the same set-up to investigate the response of the savings rate to the identified financial and uncertainty shocks. An exogenous increase in uncertainty may lead to an increase in precautionary savings. This conjecture can be evaluated by estimating another set of local projections, while using the savings rate as dependent variable. The results, also shown in Figure 9, confirm that the savings rate tends to increase after an uncertainty shock, while being broadly unaffected by financial shocks.

In sum, uncertainty shocks appear to have an inflationary impact via increased markups by firms, while they also exert a deflationary effect through increased precautionary savings by households. On balance, the overall contribution of those two opposing forces appears to be in favour of higher goods prices over the next two years. At the same time, both forces are contractionary.

V Relative importance of shocks in specific periods

V.A Forecast error variance decomposition (FEVD)

In order to assess the relative importance of the identified shocks, we compute the FEVD for each of the variables in our model. Figure 10 provides the results for the model with consumers' perceived uncertainty. Similar results with the other uncertainty measures are provided in the Appendix.

In the short-term, a substantial part of the variation in GDP is explained by demand shocks and cost-push shocks; while the variation on goods prices is mostly explained by uncertainty shocks, demand shocks and cost-push shocks.

In the long-term, instead, the variation in GDP is mostly explained by uncertainty shocks, while the variation in goods prices is mostly explained by interest rate shocks. The observation that uncertainty shocks play an important role in the dynamics of GDP corroborate the importance of exogenous changes in uncertainty on real economic activity and the need for immediate policy actions, particularly if an economy is hit by bad uncertainty, as the resulting scarring effects are detrimental. Equally important are the results of the relatively important role played by shocks to the risk-free rate on the dynamics of goods prices, and the implications for monetary policymakers to stabilise inflation through all their instruments, which can affect the long-term interest rates.

It is worth noticing that financial shocks explain the largest portion of the FEVD of corporate spreads while uncertainty shocks explain the largest portion of the FEVD of the uncertainty measure, both ranging between 50% and 60% depending on the horizon and the choice of the uncertainty measure. This outcome is in line with the intuition of Caldara et al. (2016); although, their portion of the FEVD attributable to financial and uncertainty shocks is somewhat larger, partly driven by the assumptions they maintain to identify the shocks. Overall, the results suggest that both shocks are important drivers of the business cycles in the US.

V.B Business cycle drivers during recessions

The US economy was in recession four times since 1984 according to the National Bureau of Economic Research (NBER): between July 1990 and March 1991 caused by the savings-and-loan crisis; between March 2001 and November 2001 due to the dot-com bubble; between December 2007 and June 2009 due to the national housing bubble; and since February 2020 due to the COVID-19 pandemic. The first three recessions are associated to financial markets (Ng and Wright, 2013), while the last recession in 2020 is the direct result of the COVID-19 pandemic with financial markets potentially playing a role in the transmission of the shock. The drivers of these recessions based on our model are summarised in Figure 11.

Savings-and-loan crisis. The Savings-and-loan crisis was a financial disaster resulting in the failure of thousands savings and loan associations in the United States and contributing to the recession of 1990-1991. Excessive lending and risk raking resulted from regulatory and legislative changes in the 1980s. our model suggests that adverse demand and uncertainty shocks were the main drivers of the 1990-1991 recession. Goods prices increased in this recession mainly due to the uncertainty shocks.

Dot-com bubble. The advent of the web, the elimination of commercial restrictions from the Internet and the creation of more powerful and more economical computers in the mid-1990s led to a period of frenetic growth in the computing industry generally referred to as the *dot-com boom*. The associated dot-com bubble was a stock market bubble caused by excessive speculation of internet-related companies in the late 1990s. Between 1995 and its peak in March 2000, the Nasdaq Composite stock market index rose by 400% and subsequently collapsed by 78% from its peak by October 2002, losing all its gains during the bubble. According to our model, the fall in GDP is mainly attributable to adverse uncertainty shocks and demand shocks, which also contributed to dynamics of GZ credit spreads. The role of uncertainty shocks in this recession became even more prominent after the 9/11 attacks. Goods prices tended to increase in the first part of the recession as well as in September 2001, also due to uncertainty shocks.

Global Financial Crisis (GFC). The GFC refers to a period of extreme stress in the financial sector and financial markets globally between mid-2007 and mid-2009. The downturn in the US housing market and the rising number of borrowers unable to repay their loans was a catalyst for the financial crisis. Over this period, tightened credit conditions (first moments) and increased financial stress (second moments) reinforced each other, business investment declined, and households were less willing to spend as confidence collapsed. The resulting fall in US output was, at that time, the deepest since the Great Depression in the 1930s and the recovery from GFC was much slower than the recoveries from recessions that were not associated with a financial crisis.

According to the historical decomposition of our model, a combination of both financial and uncertainty shocks, and hence a very pronounced tightening in financing conditions, contributed strongly to the fall in real GDP, while demand shocks had no role.

The historical decomposition of the price dynamics over this period are also informative. Adverse financial shocks reduced goods prices, while the adverse uncertainty shocks increased them. Given these opposite forces, the observed fall in goods prices can be attributed to the relatively higher long-term interest rates. After the collapse of Lehman Brothers, the Federal Reserve rapidly lowered the Federal Fund rate to zero, provided ample liquidity to the financial sector and purchased a substantial amount of financial securities to stimulate the economy. Yet, the 10-year US Treasury declined by only 130 basis points between September 2008 and March 2009 and this is interpreted by the model as tightening in financing conditions.

COVID-19. The COVID-19 outbreak in 2020 generated a collapse in consumption and production and a fall in consumer prices. The dominant drivers could be (i) a contraction in supply, given the nature of the disaster risk and the closure of some activities, and/or (ii) a contraction in demand given the sharp fall in consumption and the rise in savings, and/or (iii) an increase in uncertainty given the upsurge in financial markets' volatility in the first instance of the crisis.[13]

Under the hypothesis that the transmission mechanism of the shocks remained unaltered during the pandemic, we can use the estimated model over the period 1984-2019 to identify the main drivers of the business cycle fluctuations in 2020 and 2021. The historical decomposition of shocks during the COVID-19 pandemic suggests that demand and supply shocks were primary the drivers of real GDP and goods prices in 2020. Large financial shocks in March 2020 and uncertainty shocks in March and April 2020 were immediately smothered by fiscal and monetary policy interventions. The rebound during the summer of 2020 and thereafter was facilitated by very favourable financing conditions, while uncertainty about the economic outlook continued to be a drag to economic activity while pushing up goods prices (see Figure 11).

Summary. All in all, uncertainty shocks were particularly important during the first three recessions, which are associated to stress in financial markets. Interest rate shocks played a marginal role during the four recessions under consideration. Supply shocks were important at the beginning of the pandemic in 2020. Similarly, the tightening in credit conditions, proxied by higher GZ credit spreads, were partly driven by exogenous financial shocks, which were very adverse during the GFC as well as at the beginning of the COVID-19 recession in March 2020. The results corroborate the view that policymakers successfully averted a negative loop between financial and uncertainty shocks during the COVID-19 recession, allowing for an immediate rebound of the economic activity already later in 2020. This swift recovery contrasts sharply with the GFC. Similarly, the dynamics of GZ credit spreads during the savings-and-loan crisis and the dot-com bubble is explained by adverse uncertainty and demand shocks, while financial shocks counteracted them. Finally,

[13] During the January 2021 American Economic Association and American Finance Association joint panel "Effects of and lessons learned from COVID-19", chaired by Markus Brunnermeier (Princeton University) and discussed by Nicholas Bloom (Stanford University), Sydney Ludvigson (New York University) and Jeremy C. Stein (Harvard University), the following question was asked: "Given the drop in real GDP growth in 2020Q2 and the sharp rebound in 2020Q3, what are the main drivers of economic activity: supply, demand or uncertainty shocks?". Jeremy Stein replied saying that "It could be demand, it could be supply, I do not know" and Sydney Ludvigson said "I really do not know".

if recessions are accompanied by an increase in goods prices, this typically follows from the endogenous propagation of uncertainty shocks.

V.C Additional specific episodes

The 1987 Black Monday. On Monday October 19, 1987, the S&P 500 index dropped by about 20% and financial stress rose due to panic in financial markets. Technical factors contributed to the severity of the crash. The stress was so acute that there was a debate to halt trading temporarily. By the end of the month, markets had fallen considerably and the CISS had risen from 0.07 at the end of September to 0.39 in October and it continued to increase further to 0.64 in November 1987. A similar upward trend is recorded in consumers' perceived uncertainty and EPU. The 1987 stock market crash was a shock to the stability of the financial system, which impaired market functioning. In line with common wisdom (e.g. Bloom, 2009; Ludvigson et al., 2020; Caggiano et al., 2021), but endogenously determined within our model, the period between September and November 1987 is attributed to uncertainty shocks, which according to our results reached two standard deviations (see first column in Figure 12). At the same time, the response of the Federal Reserve, at the time led by Alan Greenspan, was immediate with a cut in the Federal Fund rate by 50 basis points and the provision of ample liquidity, which reduced the 10-year interest rate by about 70 basis points; thereby, engineering an expansionary monetary policy shock in support of financial markets and the entire economy. The results are robust to the use of all other uncertainty measures (see Appendix)

The 1998 LTCM collapse. Long Term Capital Management (LTCM) was a hedge fund that used leverage to multiply profits by purchasing large amounts of higher-yielding bonds and shortening an equal amount of lower-yielding bonds, betting that the yield differential would decrease over time. Some of its portfolio consisted of illiquid financial instruments. After the Asian financial crisis in the spring of 1998 spread to Russia in August 1998, the interest rate spread between the high-risk, illiquid securities and the low-risk, liquid securities rose dramatically. LTCM made large losses and was finally rescued by a creditor consortium organised by the Federal Reserve in September 1998, which reported that LTCM was worth about USD 30 million, down from USD 1.6 billion earlier in the year (Edward, 1999).

The period from July 1998 to October 1998 was characterised by tightening credit conditions with credit spreads rising by about 130 basis points and heightened financial stress with the CISS (VXO) rising from 0.01 to 0.33 (from 20 to 37), while long-term interest rates declined by about 60 basis points as investors were concerned about an economic slowdown. The dynamics of financial and uncertainty shocks in this period, which our model allows to compare, suggest that most of the observed developments should be attributed to financial shocks when using either consumers' perceived uncertainty, EPU, macroeconomic uncertainty or financial uncertainty; while, instead, uncertainty shocks appear to be the most prominent driver when using CISS (see Appendix).

The crisis was short-lived and our results suggest that the the bailout of LTCM facilitated by the Federal Reserve contained a potential credit crunch as the financial shocks turned negative by the end of the year. Our finding about the role of financial shocks is in line with Bekaert and Hoerova (2014), who assign a larger portion to the volatility premium (risk) to explain the changes in VIX during the LTCM crisis. Similarly, Ludvigson et al. (2020) do not use this event to identify the uncertainty shocks. Conversely, Bloom (2009) uses this event in his work on uncertainty, because of its agnostic approach that focuses on changes in the VXO that are at least 1.65 times the standard deviation above the average of the index.

The 2011 debt ceiling crisis. The US Constitution grants Congress the power to borrow money and thus mandates that Congress exercises control over federal debt. Rising debt levels, along with continued differences in views of fiscal policy, led to a series of contentious debt limit episodes in recent years with the 2011 debt ceiling crisis being the most prominent one. In August 2011, Standard & Poor's downgraded for the first time the AAA credit rating that the US had held for 70 years. Failing to issue new debt, the US government would have to default on its outstanding liabilities. The crisis was resolved in August 2011 when President Obama signed the Budget Control Act, which included provisions aimed at deficit reduction and allowing the debt limit to rise in three stages in August 2011, September 2011 and January 2012. Between June and August 2011, the CISS (VXO) rose from 0.01 (19) to 0.28 (35) and corporate spreads rose from 270 to 375 basis points, with the largest upsurge occurring in August.

Regardless of the uncertainty measures used, our model suggest that both financial shocks and uncertainty shocks were at play in August 2011. The 2011 debt ceiling crisis was not only characterised by uncertainty shocks (e.g. Bloom, 2009; Ludvigson et al., 2020), but also by financial shocks due to repricing of risk, which resulted in credit tightening, also for US non-financial corporations.

The 2013 taper tantrum. The taper tantrum, which followed the announcement in May 2013 that the Federal Reserve would taper its asset purchase program, caused a sharp increase in interest rates, with the 10-year US Treasury rising by 120 basis points between May and August 2013. Federal Reserve president Ben Bernanke said that the policy was dependent on incoming data, but markets interpreted this as a signal that tapering was imminent. Given that the US economy was improving, it is appropriate to ask whether the increase in interest rates was an endogenous response to other underlying macroeconomic shocks, or whether a strongly contractionary interest rate shock had taken place. This question can be addressed by extracting the size of all shocks in 2013.

The results suggest that positive demand shocks characterised the US economy in April and May 2013. At the same time, positive interest rate shocks are estimated amounting to two standard deviations in May 2013 and one standard deviation in June 2013 in line with Swanson (2020)'s results. Clearly, both positive macroeconomic developments and the a surprisingly hawkish communication by the Federal Reserve triggered the sharp rise in interest rates during the tapering tantrum period.

VI Alternative approaches

The results are robust to the identification suggested by Antolín-Díaz and Rubio-Ramírez (2018), whereby the IRFs are selected if the contribution of the selected shock to the forecast error of the selected variable is the largest in absolute value. Our variation, alternatively, does allow other shocks to have a larger contribution to the forecast error of the selected variable than the restricted shock, provided that the contribution of the other shock goes into the "wrong" direction.

The importance of this flexibility is illustrated in Figure A36 in the Appendix. In September 2001, the original approach of Antolín-Díaz and Rubio-Ramírez (2018) would restrict the monetary policy shock not to be too large because it cannot contribute more strongly to the forecast error of the uncertainty variable than the uncertainty shock, while our approach estimates a fairly large coincident expansionary monetary policy shock in September 2001 that may contribute more strongly, but negatively, to the forecast error of uncertainty variable compared to the uncertainty shock itself. This feature allows monetary policy to be identified as very expansionary and, as a result, counteract immediately the adverse effects of the restricted shocks

Moreover, our variant of the narrative sign restrictions also alleviates an implicit restriction on the size of the uncertainty shock. By facilitating a strongly expansionary monetary policy shock that is estimated to lower the uncertainty variable, given the size of the forecast error, there is more room for a larger uncertainty shock to contribute more positively to the uncertainty variable than in the absence of the counteracting monetary policy shock, as would be the case in the original set-up of the narrative sign restrictions.

Second, we have also used the method suggested by Brunnermeier et al. (2021), where shocks are statistically identified by heteroskedasticity of the shocks across different regimes. In our application of Brunnermeier et al. (2021), we have used either the consumers' perceived uncertainty (see Figure A33 in Appendix) or the CISS index (see Figure A34 in Appendix) to measure uncertainty. The other variables in the VAR are the same as in our baseline specification and we apply the same volatility regimes as in Brunnermeier et al. (2021) with four distinct regimes in our sample, starting in January 1984, December 1989, December 2007 and December 2010.

As in Brunnermeier et al. (2021), we find that the innovations mostly associated to our financial variable reduce output and goods prices. However, in contrast to many results in the empirical literature, the innovation that is most strongly associated to our uncertainty variable has no discernible impact on output, suggesting that the uncertainty shock may not be adequately recovered in this model.

VII Conclusions

Disentangling the drivers of business cycle fluctuations in real time is of utmost importance, because they imply different policies. Macroeconomic textbooks suggest the use of counter-cyclical (i) traditional fiscal and monetary counter-cyclical policies if the cycle is driven by demand shocks, (ii) insurance-type fiscal (i.e. payroll support, tax cuts and moratoria), macroprudential (i.e. dividend policies) and monetary (i.e. purchase of government and corporate bonds) policies against tail risks if the cycle is driven by uncertainty shocks, and (iii) monetary and macroprudential policies if the cycle is driven by financial shocks (i.e. unconventional liquidity operations).

We jointly identify demand, financial and uncertainty shocks together with interest rate shocks and cost-push shocks, using a variant of the narrative restriction identification à la Antolín-Díaz and Rubio-Ramírez (2018), where, at a given date, some of the unrestricted shocks are allowed to have a stronger contribution to the unforecastable change of the variable of interest if they shift the variable in the opposite direction compared to the contribution of the restricted shock.

Using a variety of uncertainty measures used in the literature, we find that financial shocks reduce output and goods prices, while uncertainty shocks reduce output but tend to increase goods prices. In response to uncertainty shocks, firms increase their markups, in line with the theory of self-insurance against being stuck with too low a price, and households tend to increase their savings rate as an edge for income risk. Both decisions are contractionary, but prices tend to increase on aggregate, This explains why goods prices increase at the onset of a recession originated in financial markets. We also find that sharply higher macroeconomic uncertainty in recession is partly an endogenous response to demand and financial shocks. Financial and uncertainty shocks explain a large fraction of fluctuations in output and prices during the 2008-2009 crisis, while cost-push and demand forces prevail during the COVID-19 pandemic.

Finally, we also show the importance of identifying financial and uncertainty shocks along with other standard macroeconomic shocks. A large part of the literature on financial shocks and uncertainty shocks relies on evidence derived from partially identified VARs by leaving some of the shocks in the system unidentified. While this may be a harmless decision for point-identified VARs, this modelling choice can represent an important drawback in the case of set-identified VARs.

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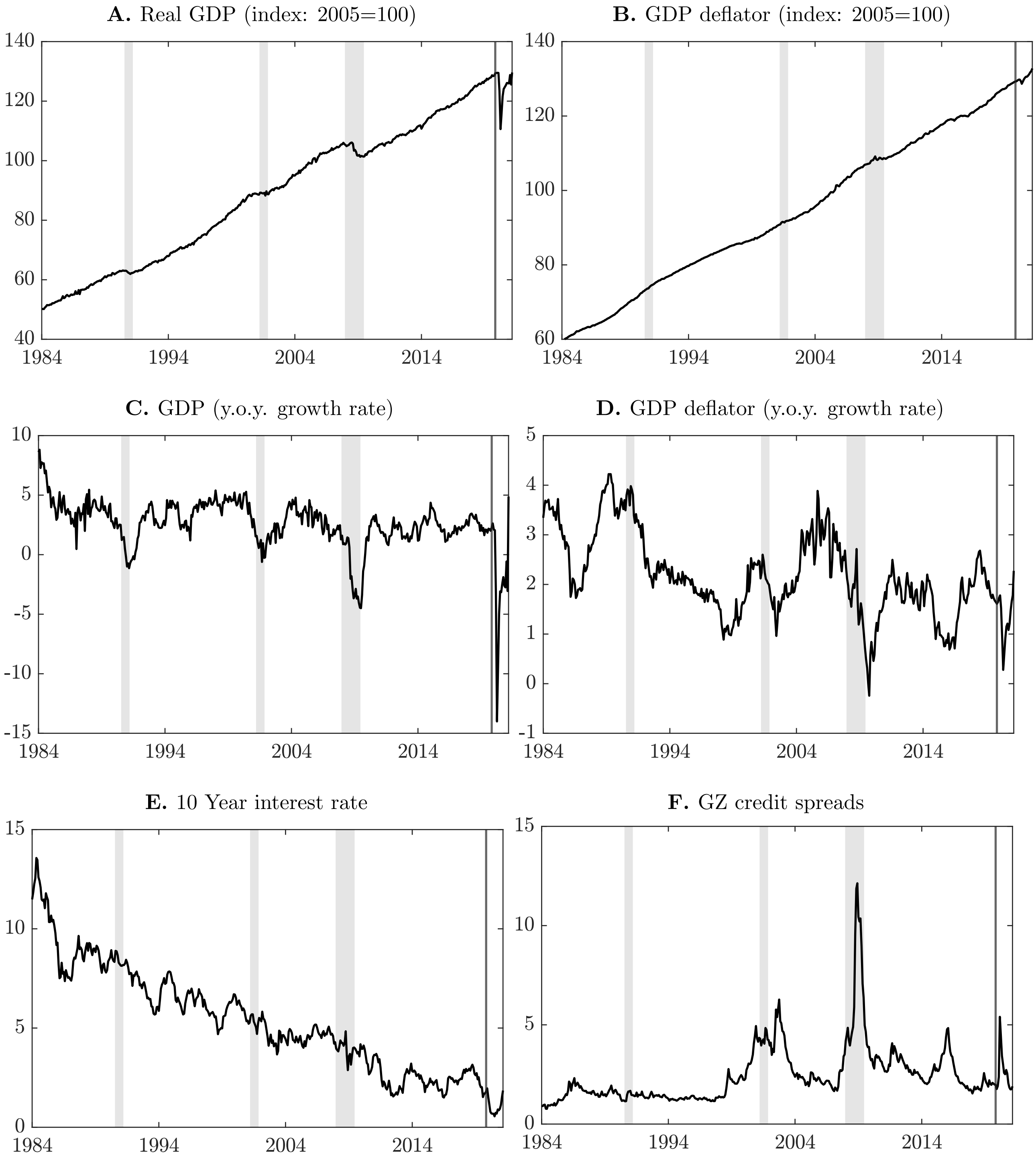
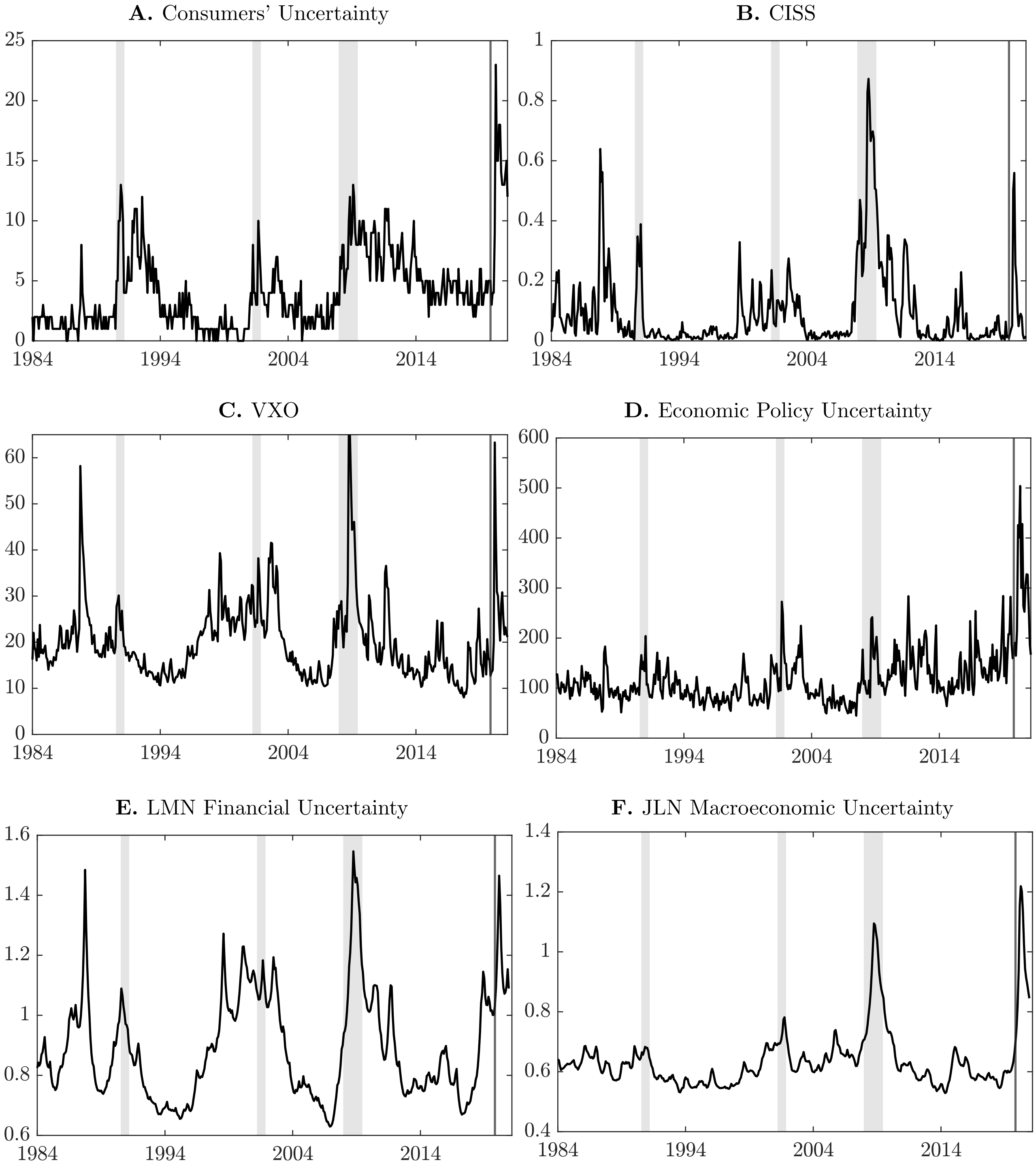
Tables and Figures

Figure 1: GDP, GDP Deflator, Interest Rate and GZ Credit Spreads



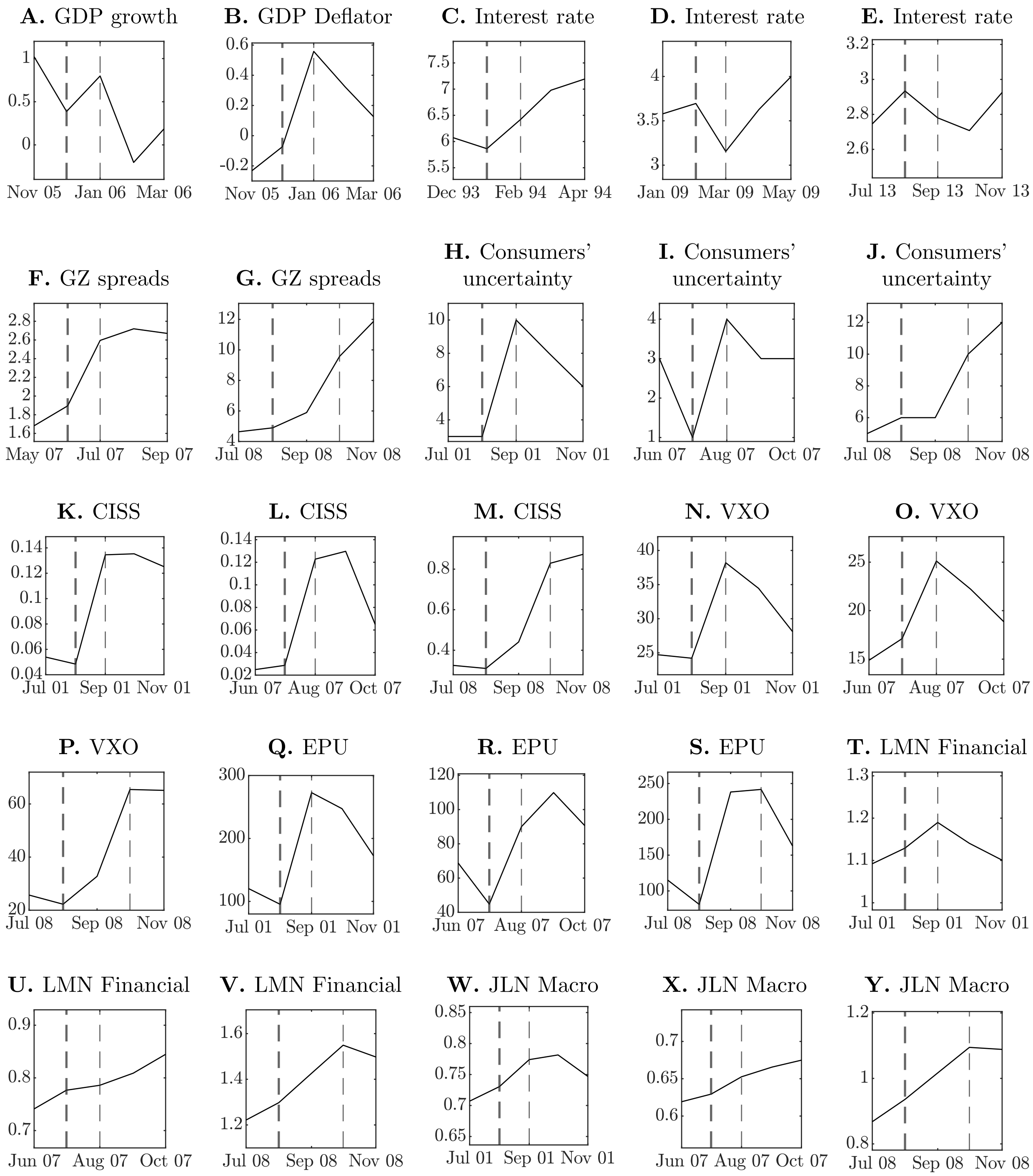
Notes: The GZ corporate credit spread is constructed using the approach suggested by Gilchrist et al. (2009) and Gilchrist and Zakrajšek (2012). The vertical line indicates the end of the estimation sample; the shaded areas represent NBER recessions.

Figure 2: Alternative Uncertainty Measures



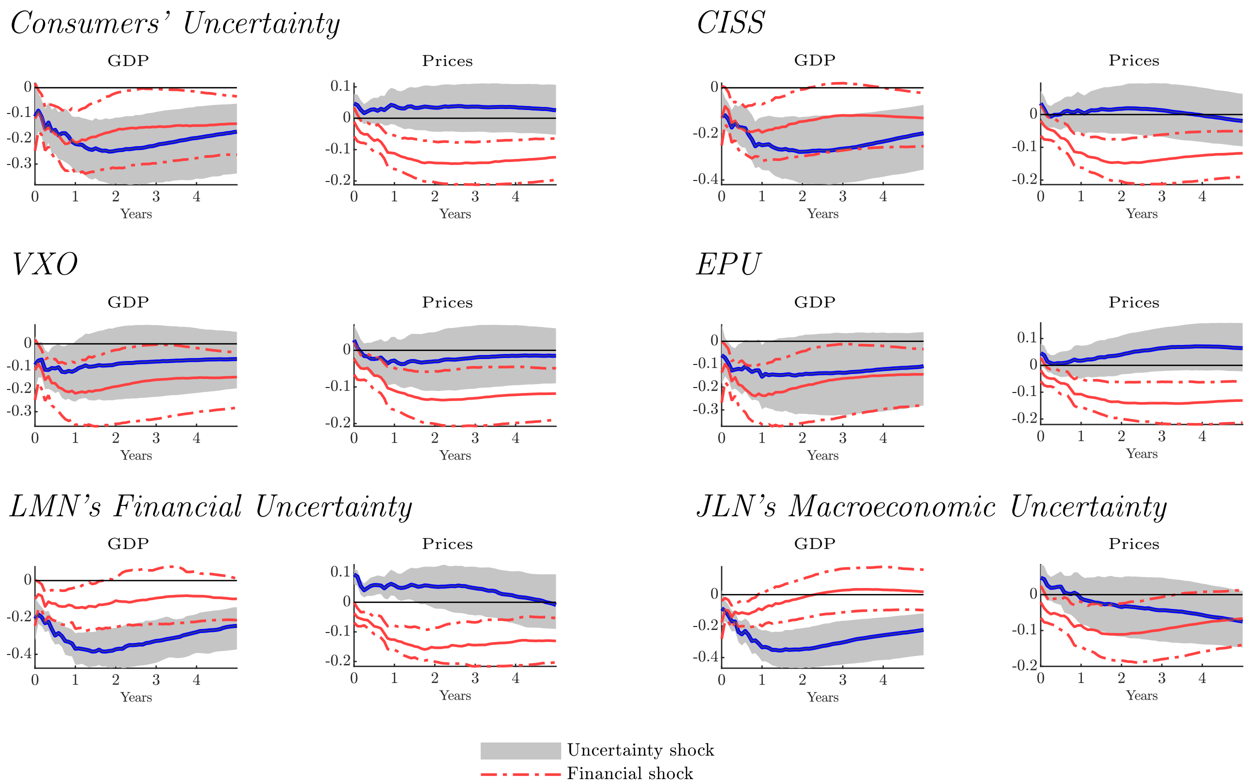
Notes: The consumers' perceived uncertainty is the measure suggested by Leduc and Liu (2016). The US Composite Indicator of Systemic Stress (CISS) is the measure suggested by by Kremer et al. (2012). The VXO is the stock market volatility suggested by Bloom (2009). The economic policy uncertainty (EPU) is the measure suggested by Baker et al. (2016). The LMN financial uncertainty is the measure suggested by Ludvigson et al. (2020). The JLN macroeconomic uncertainty is the measure suggested by Jurado et al. (2015).

Figure 3: Events and Narrative Restrictions



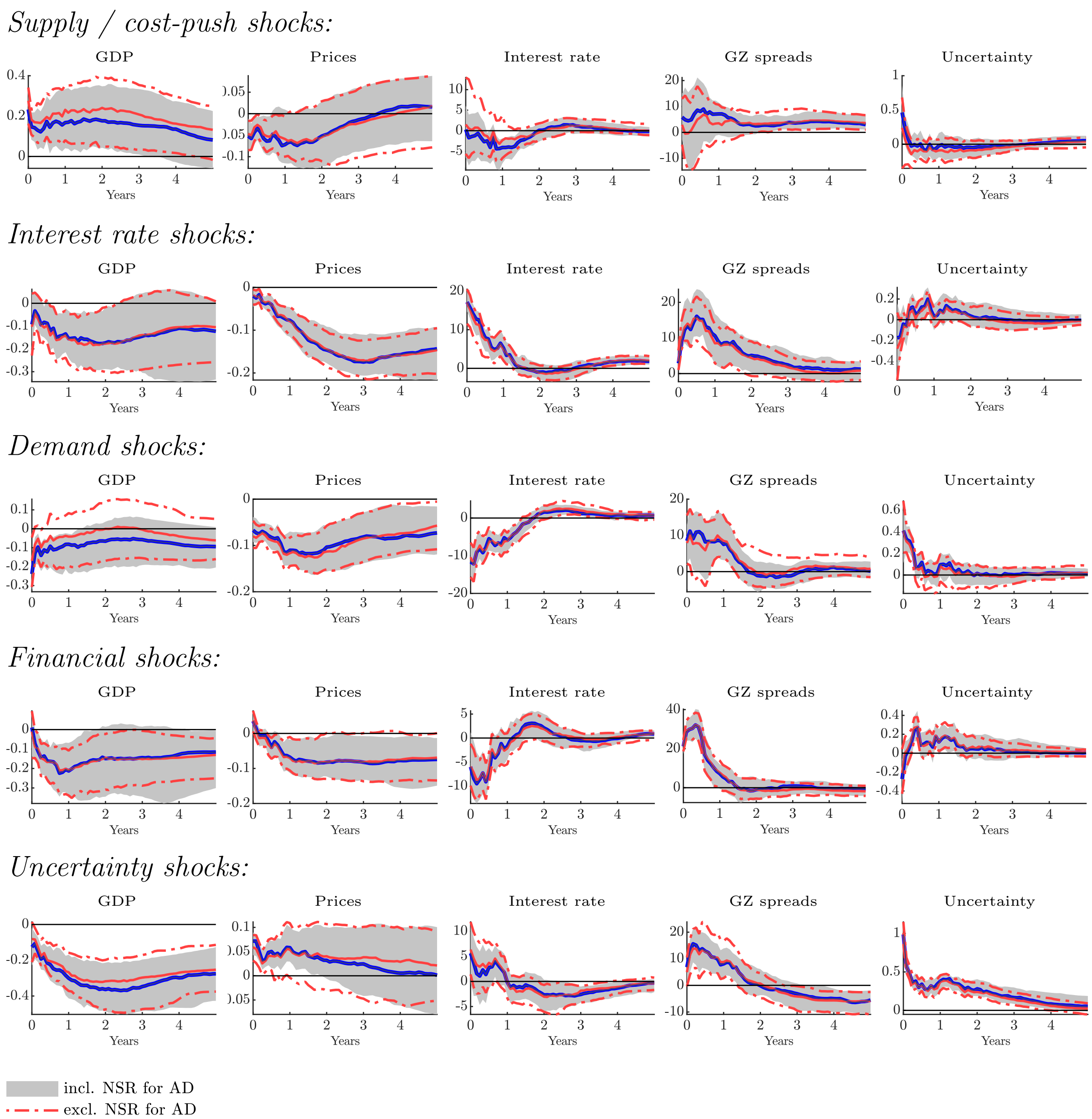
Notes: The two dashed lines delineate the periods over which the narrative restrictions are imposed.

Figure 4: IRFs when only Two Shocks are Identified



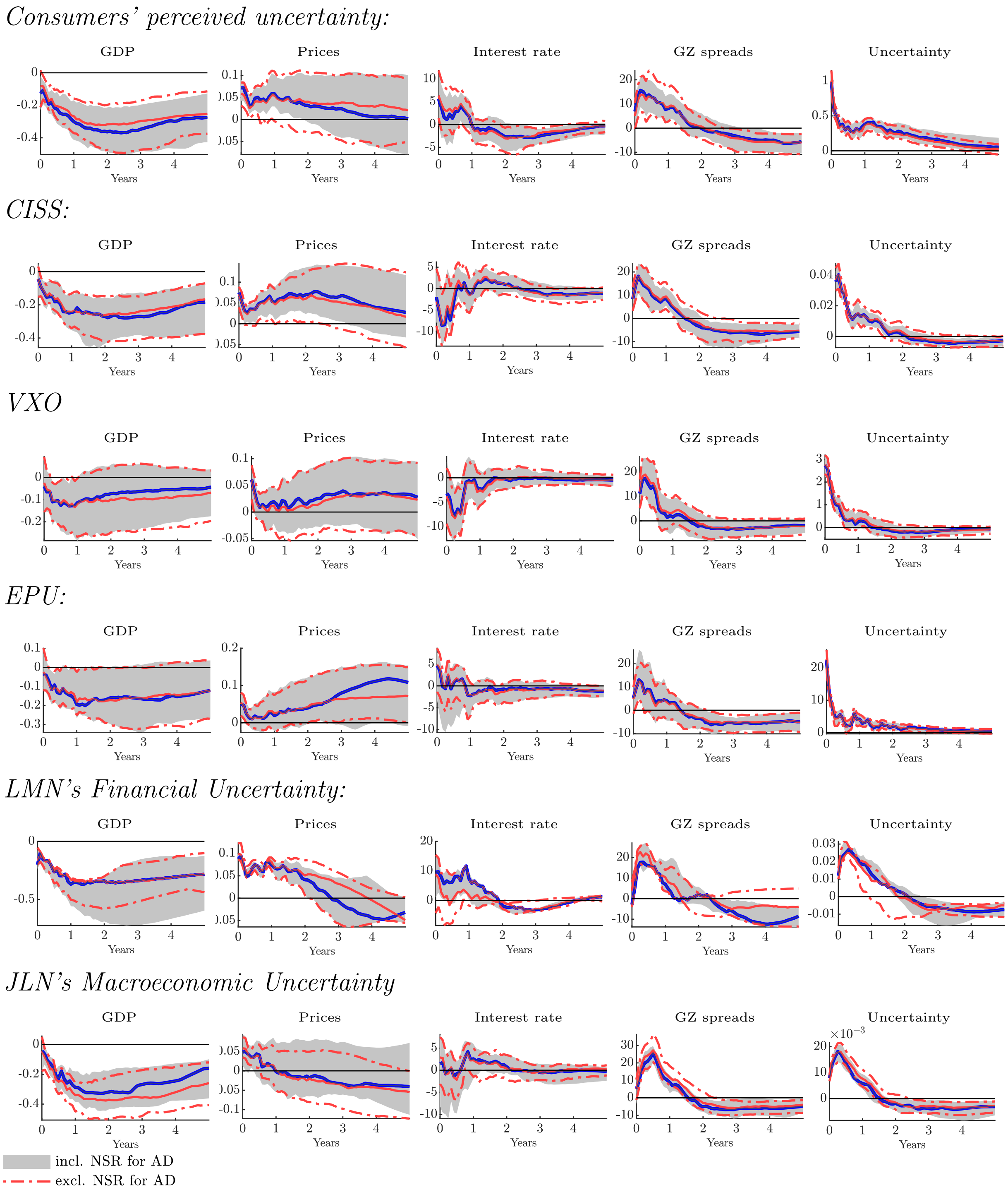
Notes: The represented VARs contain five variables: GDP, goods prices, 10-year US Treasury rate, GZ credit spreads and either one of the uncertainty variables. The identification of the shocks draws exclusively on the narrative restrictions for the financial shock and the uncertainty shock in addition to a normalization of the impact response of GZ spreads after a financial shock and the impact response of the uncertainty variable after an uncertainty shock.

Figure 5: Macroeconomic Responses to Shocks using Consumers' Uncertainty (IRFs)



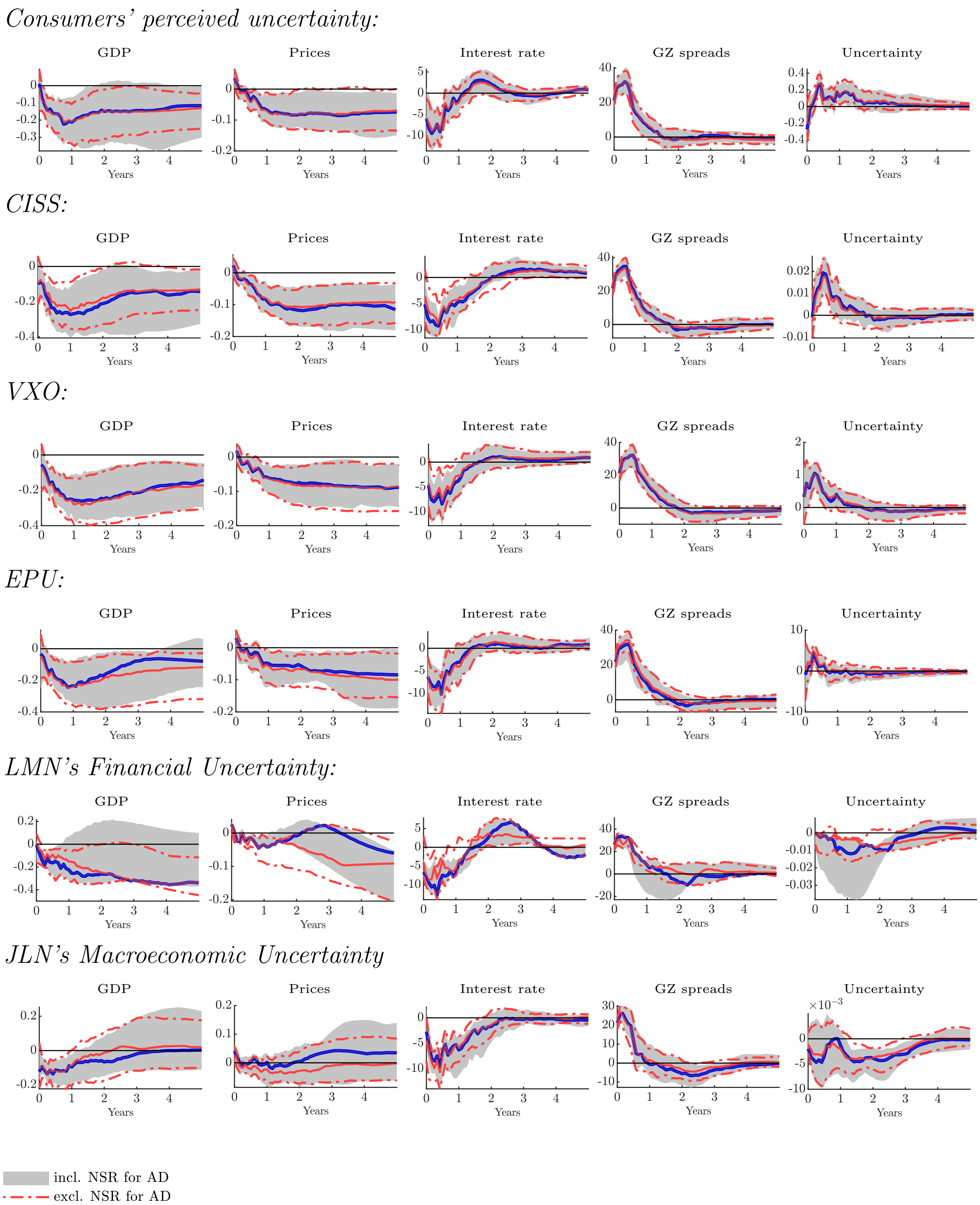
Notes: The VAR contains five variables: GDP, goods prices, 10-year US Treasury, GZ credit spreads and consumers' uncertainty. Five shocks are identified using the identification in Table 1. The median IRFs in blue and the corresponding posterior 68% credible sets (shaded grey area) are obtained by using all narrative restrictions described in Table 1 for identification. The median IRFs in red and the corresponding posterior 68% credible sets (dashed red lines) are are obtained by using all narrative restrictions for identification, except for the narrative on demand.

Figure 6: Impact of Uncertainty Shocks using various Uncertainty Gauges (IRFs)



Notes: Each of the represented VARs contains five variables: GDP, goods prices, 10-year US Treasury, GZ credit spreads and one of the alternative uncertainty proxies, which are used to identify the uncertainty shocks. Five shocks are identified, that is, supply shocks, interest rate shocks, demand shocks, financial shocks and uncertainty shocks using the identification in Table 1. The median IRFs in blue and the corresponding posterior 68% credible sets (shaded grey area) are obtained by using all narrative restrictions described in Table 1 for identification. The median IRFs in red and the corresponding posterior 68% credible sets (dashed red lines) are are obtained by using all narrative restrictions for identification, except for the narrative on demand.

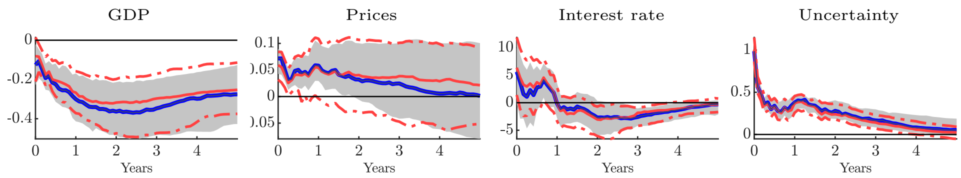
Figure 7: Impact of Financial Shocks using various Uncertainty Gauges (IRFs)



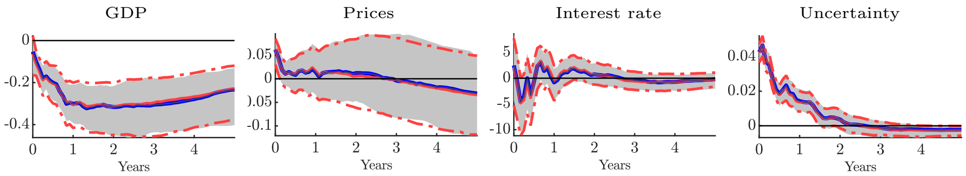
Notes: Each of the represented VARs contains five variables: GDP, goods prices, 10-year US Treasury, GZ credit spreads and one of the alternative uncertainty proxies, which are used to identify the uncertainty shocks. Five shocks are identified, that is, supply shocks, interest rate shocks, demand shocks, financial shocks and uncertainty shocks using the identification in Table 1. The median IRFs in blue and the corresponding posterior 68% credible sets (shaded grey area) are obtained by using all narrative restrictions described in Table 1 for identification. The median IRFs in red and the corresponding posterior 68% credible sets (dashed red lines) are are obtained by using all narrative restrictions for identification, except for the narrative on demand.

Figure 8: Impact of Uncertainty Shocks using various Proxies and excluding GZ Spreads (IRFs)

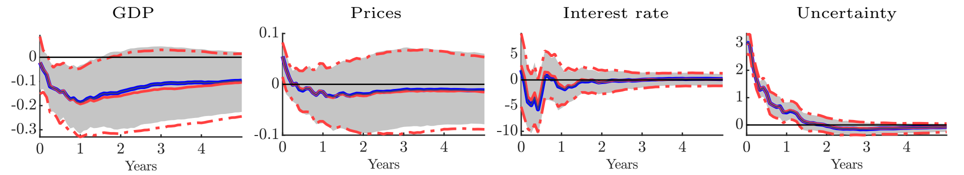
Consumers' perceived uncertainty:



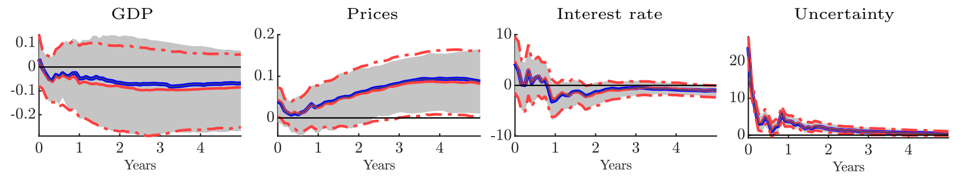
CISS:



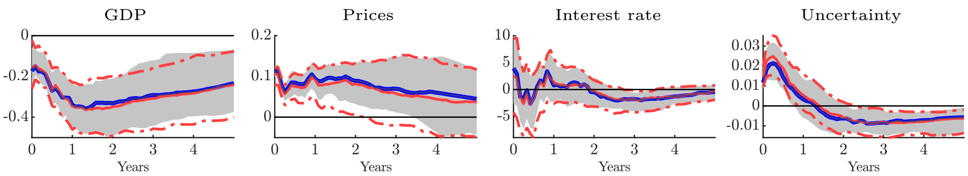
VXO:



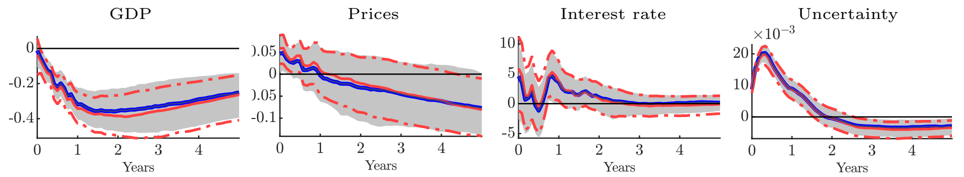
EPU:



LMN's Financial Uncertainty:



JLN's Macroeconomic Uncertainty

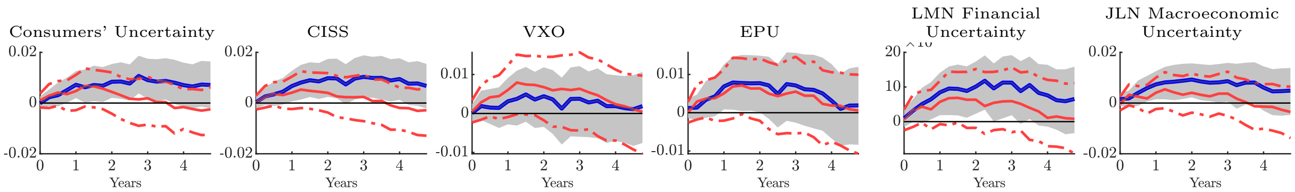


incl. NSR for AD
excl. NSR for AD

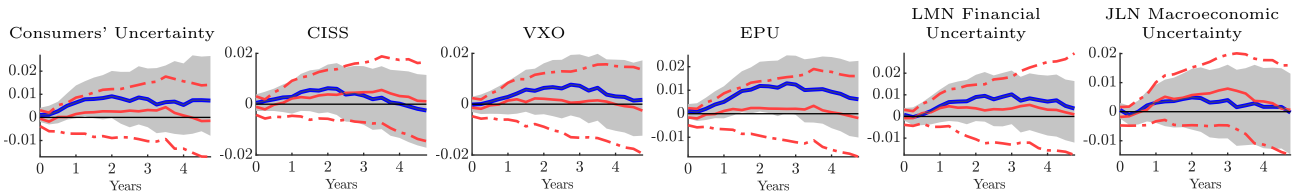
Notes: Each of the represented VARs contains four variables: GDP, goods prices, 10-year US Treasury and one of the alternative uncertainty proxies, which are used to identify the uncertainty shocks. Four shocks are identified, that is, supply shocks, interest rate shocks, demand shocks and uncertainty shocks using the identification in Table 1. The median IRFs in blue and the corresponding posterior 68% credible sets (shaded grey area) are obtained by using all narrative restrictions described in Table 1 for identification. The median IRFs in red and the corresponding posterior 68% credible sets (dashed red lines) are are obtained by using all narrative restrictions for identification, except for the narrative on demand.

Figure 9: Impact of Uncertainty Shocks on Markups and Savings Rate: Local Projections

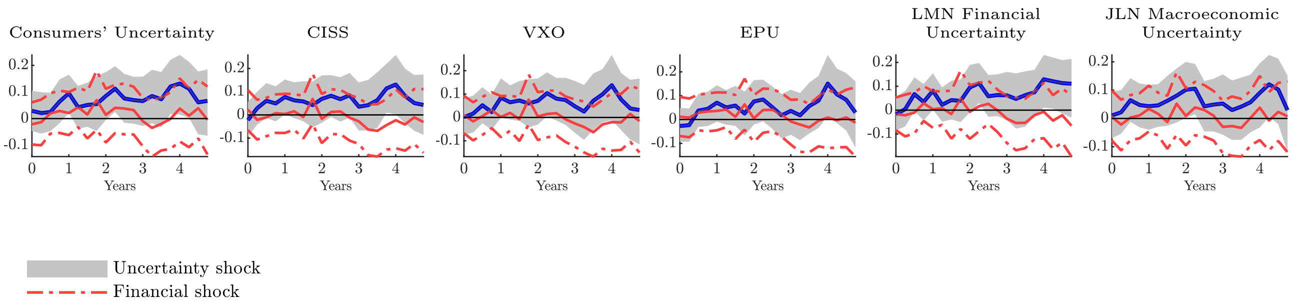
Markup measure 1:



Markup measure 2:

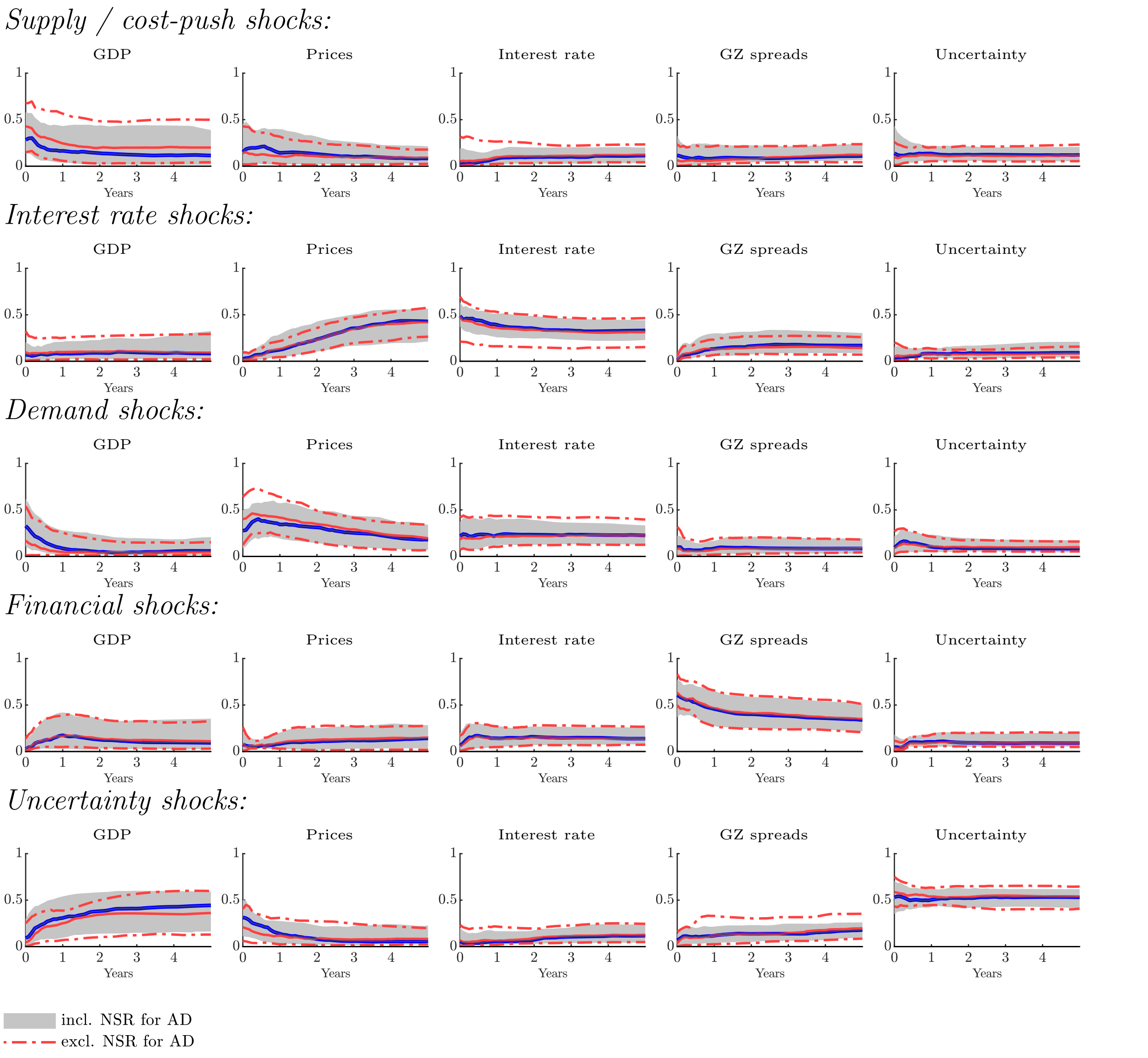


Savings rate:



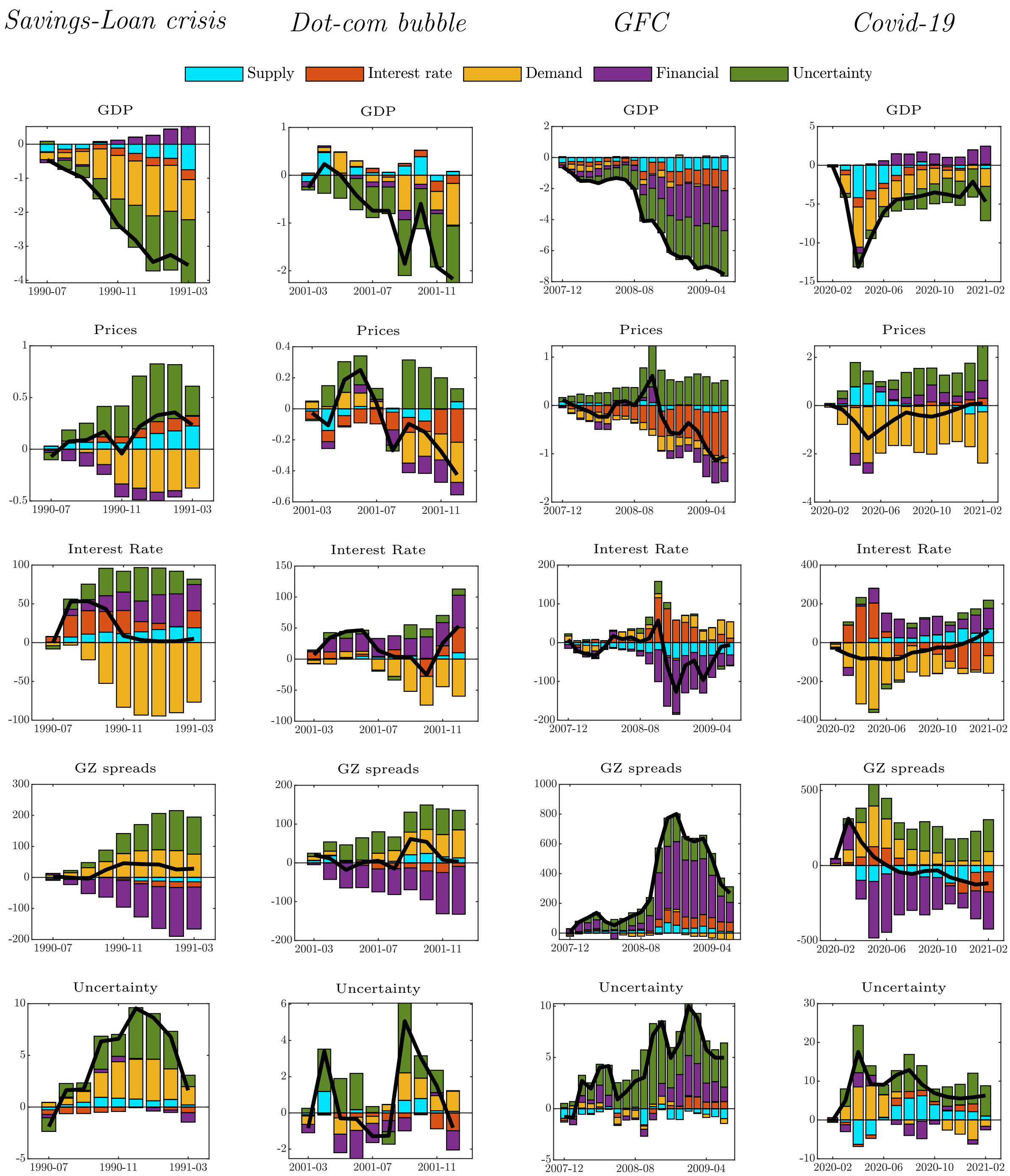
Notes: Median IRFs and 90% confidence bands. The error bands are constructed by, first, obtaining the point estimates of the Local Projection coefficients for each posterior draw of the structural shock time series and simulating the estimation uncertainty associated with those point estimates by generating 100 draws from their respective asymptotic distribution. Next, by executing this simulation for all N draws of the posterior of the structural shocks, the collection of $100 \cdot N$ draws encompasses the estimation uncertainty from the Local Projections as well as the uncertainty that arises from using an estimated shock series as regressor. The selected markup measures are the two preferred measures in Nekarda and Ramey (2020): they are based on a CES production function where the markup is computed from the output-capital ratio. Markup measure 2, in addition, accounts for the presence of nonproductive or overhead labor, while markup measure 1 does not.

Figure 10: Forecast Error Variance Decomposition using Consumers' Uncertainty



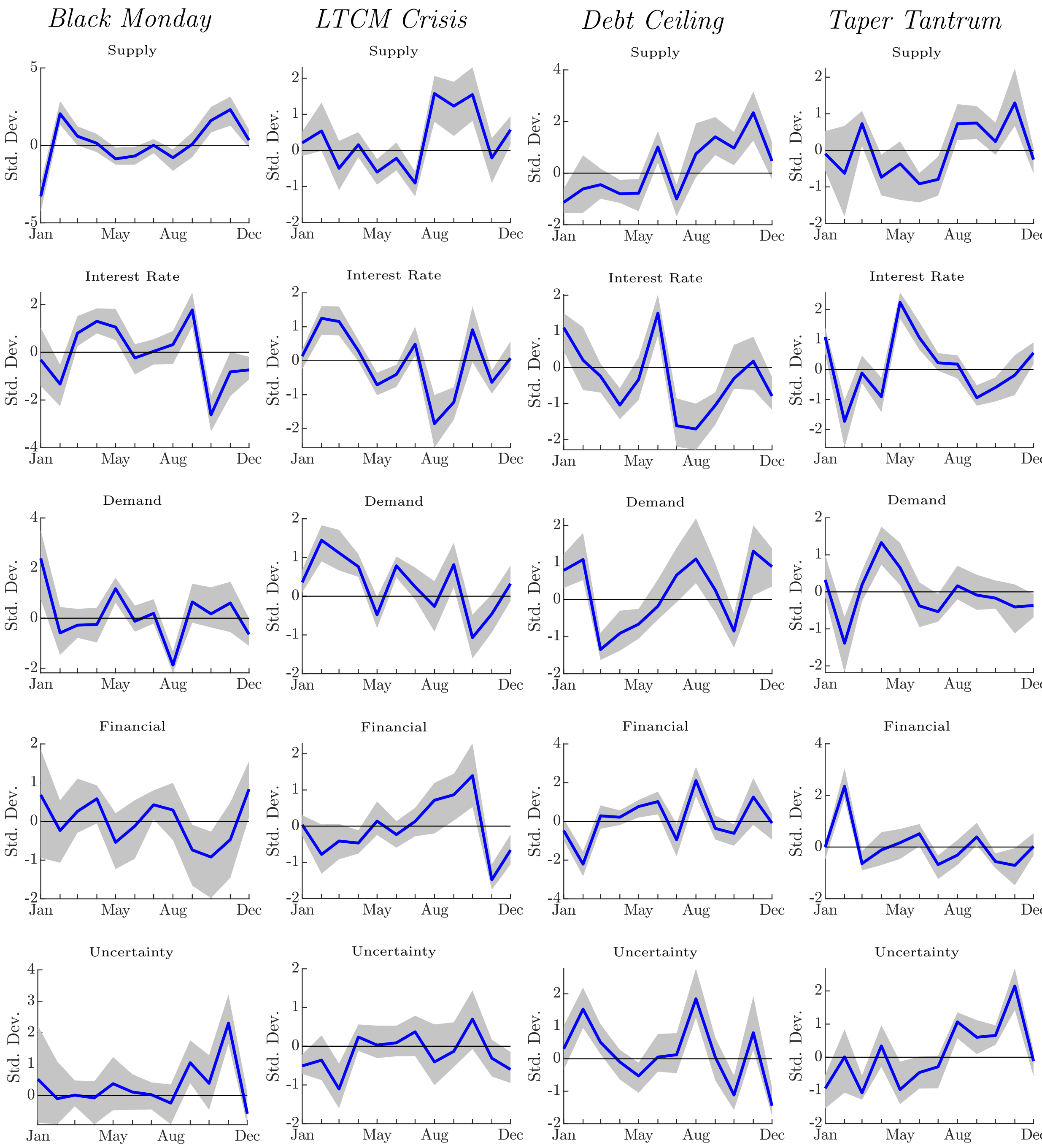
Notes: The VAR contains five variables: GDP, goods prices, 10-year US Treasury, GZ credit spreads and consumers' uncertainty. Five shocks are identified using the identification in Table 1. The median FEVDs in blue and the corresponding posterior 68% credible sets (shaded grey area) are obtained by using all narrative restrictions described in Table 1 for identification. The median FEVDs in red and the corresponding posterior 68% credible sets (dashed red lines) are are obtained by using all narrative restrictions for identification, except for the narrative on demand.

Figure 11: Historical Decomposition during Recessions using Consumers' Uncertainty



Notes: The VAR contains five variables: GDP, goods prices, 10-year US Treasury, GZ credit spreads and consumers' uncertainty. Five shocks are identified using the identification in Table 1 with all narrative restrictions.

Figure 12: Structural Shocks in Selected Periods using Consumers' Uncertainty



Notes: The VAR contains five variables: GDP, goods prices, 10-year US Treasury, GZ credit spreads and consumers' uncertainty. Five shocks are identified using the identification in Table 1 with all narrative restrictions.