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Deflationary financial shocks and  
inflationary uncertainty shocks:  
an SVAR investigation

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## Abstract

What are the economic implications of financial and uncertainty shocks? 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 may increase at the onset of a recession and are not accompanied by pronounced deflationary pressures. The two shocks are identified jointly with an approach that is less restrictive than Antolín-Díaz and Rubio-Ramírez's method.

**Keywords:** Business cycles, financial shocks, uncertainty shocks, SVAR, narrative identification

**JEL Classification:** C32, E32

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## Non-technical summary

Disentangling the drivers of business cycle fluctuations is of utmost importance, because they imply different policies. The literature suggests the use of

- traditional fiscal and monetary counter-cyclical policies, if the cycle is driven by demand shocks;
- 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
- monetary and macroprudential policies, if the cycle is driven by financial shocks (i.e. unconventional liquidity operations).

However, the economic profession is involved in a heated discussion about the macroeconomic implications of financial and uncertainty shocks. While macroeconomic evidence on the contractionary effect of both shocks is plentiful, the effects on goods prices, in particular for uncertainty shocks are often not investigated. Therefore, it is important to distinguish a financial shock from an uncertainty shock.

A financial shock corresponds to an unexpected worsening of conditions in credit markets with tightness in business financing and repricing of risks, which it is typically captured by corporate credit spreads. Uncertainty is more elusive and there is little consensus on a preferred measure. It is the result of random economic events that make the economic outlook less predictable. Lower uncertainty is associated to lower volatility, smaller forecast errors and higher economic growth; while higher uncertainty indicates higher volatility, larger forecast errors and eventually results in lower economic growth.

We jointly identify demand, financial and uncertainty shocks together with interest rate shocks and cost-push shocks. Using a variety of uncertainty measures used in the literature, we find that financial shocks are deflationary, 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 inflationary effect of uncertainty shocks has contributed substantially positively to the price dynamics in the US recessions since 1984 contributing to the “missing disinflation” after the global financial crisis, lending credence to the upward pricing bias in the firm’s optimization problem.

Apart from disentangling the drivers of recessions, through the lenses of our model, we also look at the economic forces at play during key economic events in our sample. In that respect, we ask our model what the structural shocks are that constituted the collapse of the Long Term Capital Management (LTCM) in 1998, the September 11th terrorist attacks in 2001, the 2011 debt ceiling crisis and the 2013 taper tantrum. Particularly, during the

taper tantrum period in 2013, we find that both positive macroeconomic developments and a surprisingly hawkish communication by the Federal Reserve triggered the sharp rise in long-term interest rates.

# I Introduction

The economic profession is involved in a heated discussion about the macroeconomic implications of financial and uncertainty shocks. While macroeconomic evidence on the contractionary effect of both shocks is plentiful, the effects on goods prices, in particular for uncertainty shocks, are often not investigated. Typically, uncertainty and financial shocks are identified separately, due to the intrinsic empirical difficulty to separate the one from the other. Using a Bayesian Structural Vector Autoregression (SVAR) for the United States (US) from 1984 until 2019, we propose a new set of identifying restrictions to single out the causal effect of both shocks on aggregate economic variables, where financial shocks relate to an unexpected worsening of conditions in credit markets and uncertainty shocks are the result of random economic events, which make the economic outlook less predictable. We are agnostic about the transmission mechanism of both shocks, which are identified exclusively with narrative restrictions, using an approach that is less restrictive than the method proposed by Antolín-Díaz and Rubio-Ramírez (2018, henceforth, AR18).

We find that an exogenous tightening of financial conditions causes a decline in output and goods prices, while an exogenous increase in economic uncertainty causes a decline in output and an increase in goods prices. The deflationary effect of adverse financial shocks is more in line with traditional demand side transmission, in contrast to the supply-side channels that have been postulated more recently to rationalize the appearance of the “missing disinflation” puzzle during the Great Recession in 2008-09 (Gilchrist et al., 2017; Christiano et al., 2015).<sup>1</sup> The inflationary effect of uncertainty shocks, on the other hand, contributed substantially positively to the price dynamics in the most recent US recessions as well as to the missing disinflation during the global financial crisis, lending credence to the upward pricing bias in the firm’s optimization problem; that is, firms self-insure against being stuck with too low a price in the future should a recession not materialize by preemptively raising markups (see, e.g., Born and Pfeifer, 2014; Fernández-Villaverde et al., 2015; Bonciani and van Roye, 2016; Fasani and Rossi, 2018). We corroborate the upward pricing bias by showing, through local projections, that firms increase their markups in response to the identified

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<sup>1</sup>US inflation in 2008-09 failed to fall as much as expected given the depth of the recession (e.g., Hall, 2011).

uncertainty shocks.<sup>2</sup> In addition, the local projections also suggest that uncertainty shocks induce a precautionary savings effect, as the household savings rate tends to increase after an uncertainty shock. Overall, we confirm that both financial shocks and uncertainty shocks are quantitatively non-negligible drivers of output and prices. These conclusions can be drawn irrespective of whether the employed uncertainty measure is obtained from surveys, financial variables or macroeconomic variables.

This paper contributes to the existing literature on financial and uncertainty shocks in three ways. First, while a large share of the existing theoretical and empirical models considers either shock in isolation,<sup>3</sup> we argue that the simultaneous identification of both financial and uncertainty shocks can contribute to our understanding of their economic consequences. In particular, the causal effects of uncertainty (financial) shocks that are identified in isolation, i.e., without controlling for a potentially endogenous response of the uncertainty (financial) variable to the financial (uncertainty) shock, may reflect a combination of the causal effect of the two distinct shocks and lead inference astray. As an illustration, Christiano et al. (2014) observed that a direct impact on credit conditions may be crucial in explaining the strong macroeconomic effects of uncertainty shocks. Therefore, identifying the financial shocks without controlling for the direct effect of uncertainty shocks on credit spreads would result in attributing part of the uncertainty shocks to the financial shocks.

Second, we allow financial conditions and uncertainty to immediately respond to financial and uncertainty shocks and to other macroeconomic shocks; without restricting the impulse response functions of either shock.<sup>4</sup> This allows us to remain entirely agnostic with respect to the macroeconomic propagation of both shocks while avoiding hard-to-defend exclusion restrictions. Instead, and closely related to the approaches in Ludvigson et al. (2021) and Caggiano et al. (2021), we rely on specific historical episodes for which the econometrician

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<sup>2</sup>Lindé et al. (2016) and Fratto and Uhlig (2020) rely on large offsetting positive price markup shocks in the Smets and Wouters (2007) benchmark model to explain the missing disinflation puzzle. Alternative explanations are offered by Harding et al. (2022), who introduce non-linearities in the demand elasticity for intermediate goods implied by the Kimball aggregator; by Christiano et al. (2015); Gilchrist et al. (2017) using inflationary financial shocks; and, for the Euro Area, by Peersman (2022) through food price shocks.

<sup>3</sup> See, e.g., Bloom (2009), Gilchrist and Zakrajšek (2012), Bachmann et al. (2013), Caggiano et al. (2014), Jurado et al. (2015), Segal et al. (2015), Fernández-Villaverde et al. (2015), Baker et al. (2016), Leduc and Liu (2016), Scotti (2016), Chavleishvili and Manganelli (2019), Haque and Magnusson (2021). These papers identify one shock using a recursive method. Financial and uncertainty shocks are instead jointly identified by Caldara et al. (2016), Furlanetto et al. (2019), Brianti (2021), and Caggiano et al. (2021).

<sup>4</sup>Alternative approaches are discussed in Caldara et al. (2016), Brianti (2021), Furlanetto et al. (2019) and Caggiano et al. (2021).

has extraneous knowledge about the macroeconomic drivers at play at the time. More specifically, set-identification of the financial and uncertainty shocks results exclusively from the assumption that (i) the risk repricing in July 2007 was a credit tightening shock that dominated the contribution of other shocks to the unforecastable increase of corporate credit spreads in that month; and that (ii) Black Monday in October 1987, the liquidity crisis in August 2007 and (in the robustness section) the 9/11 terrorist attacks are uncertainty shocks that dominated the contribution of other shocks to the unforecastable increase of the uncertainty variable on those dates.

As the identifying information that we bring to the model allows us to be agnostic *ex ante* with respect to the contemporaneous effect that the other shocks in the VAR may have on uncertainty and financial conditions, we observe that about 50 to 60% of the one-month ahead unforecastable shifts in uncertainty and financial conditions are attributable to their respective endogenous responses to other shocks. This finding invalidates some of the exclusion restrictions that have been used in previous empirical work (see footnote 3). Assuming the absence of a contemporaneous effect of surprises in the other variables of the VAR on the financial or uncertainty gauges will result in mistakenly attributing their endogenous responses to exogenous variation.

Third, methodologically, we modify the method of AR18 and make it less restrictive, by removing a restriction on the relative sizes of the various shocks on the dates where we impose narrative shock restrictions. We do not require the restricted shock to be the single most important contributor (in absolute value) to the unforecastable component of the selected variable as proposed by AR18. Instead, our narrative restrictions are sign-dependent: we impose that the restricted shock, among the shocks that move the selected variable's forecast error in the same direction, is the most important contributor to this forecast error. Thereby, we allow the unrestricted shocks to exert an even stronger effect on the selected forecast error, as long as the contribution of those shocks has the opposite sign of the contribution of the restricted shock. This flexibility may be an important extension to allow the researcher to apply narrative shock restrictions to an economic event that constitutes more than one important driver of the macroeconomic dynamics at the time. For example, not only was the Black Monday shock in October 1987 a major uncertainty event, but to the extent that

the monetary policy response was more forceful than the model-implied policy rule, it also constituted a strongly expansionary monetary policy shock. Such a strong and offsetting policy response is facilitated in our modification of the AR18 approach. In addition, the flexibility of our model allows one to impose two narrative restrictions on the same variable at the same time and an example is provided in Section VII, where the cross-narrative restrictions are discussed.

Our main results are reinforced when complementing our model to single out other macroeconomic shocks such as interest rate shocks, demand shocks and cost-push shocks. We show that a narrative shock restriction on the aggregate demand shock in January 2006 has the benefit of reducing model uncertainty and sharpening inference. This approach contrasts with the vast majority of the related literature, where some shocks in the system are left unidentified. Canova and Paustian (2011) suggest that inference can be improved upon by identifying other macroeconomic shocks even if they are not essential for the analysis. We show that the impact of uncertainty shocks on goods prices is much less clear if the other shocks are left unidentified.

The paper is structured as follows. Section II discusses the economics of financial and uncertainty shocks in the context of the literature. Section III describes the shock identification strategy and the dataset. Section IV presents the key results. Sections V and VI show the implied business cycle drivers during recessions and the taper tantrum. Section VII discusses the flexibility of the model and the use of a cross-narrative restriction. Section VIII investigates the robustness of our results. Section IX concludes.

## **II On the financial and uncertainty shocks**

A financial shock corresponds to an unexpected worsening of conditions in credit markets with tightness in business financing and repricing of risks, which is typically captured with the so-called Gilchrist-Zakrajšek (GZ) corporate credit spread (Gilchrist et al., 2009). While financial shocks are unquestionably recessionary, the response of inflation depends on the relative importance of different transmission channels. On the one hand, transmission via aggregate demand due to the reallocation of consumption and investment may reduce output



and prices, as is the case for the spread shocks in, e.g., Smets and Wouters (2007), Ajello (2016), and Del Negro et al. (2015). Alternatively, inflationary transmission channels of financial shocks have been postulated by Christiano et al. (2015), where corporate borrowing rates have a direct impact on firms' marginal costs; and by Gilchrist et al. (2017) and Brianti (2021), where stickiness in firms' customer bases introduces an additional intertemporal trade-off for the firm between current cash flows and future market shares, so that firms may accommodate any reduced access to external finance by increasing cash-flow (internal funds) through higher prices.

Uncertainty is more elusive and there is little consensus on a preferred measure.<sup>5</sup> It is the result of random economic events that make the economic outlook less predictable. Lower uncertainty is associated to lower volatility, smaller forecast errors and higher economic growth; while higher uncertainty indicates higher volatility, larger forecast errors and eventually results in lower economic growth. Different approaches have been used for its quantification. Some authors use asset prices, such as the stock market volatility (Bloom, 2009; Caldara et al., 2016; Cascaldi-Garcia and Galvao, 2021; Haque and Magnusson, 2021) or the Composite Indicator of Systemic Stress (CISS) (Chavleishvili and Manganelli, 2019), others use surveys (Leduc and Liu, 2016), news-based indices (Baker et al., 2016; Larsen, 2021; Cascaldi-Garcia and Galvao, 2021), forecast errors (Rossi and Sekhposyan, 2015; Scotti, 2016), the cross-sectional dispersion of firms' sales or productivity (Bloom, 2009; Bloom et al., 2018), or a statistical model featuring stochastic volatility (Jurado et al., 2015; Mumtaz and Theodoridis, 2018; Alessandri and Mumtaz, 2019; Ludvigson et al., 2021; Carriero et al., 2018; Shin and Zhong, 2020).

The output effects are usually recessionary and can emerge or be reinforced via different transmission channels, such as factor adjustment frictions that can result in wait-and-see effects (Bloom, 2009; Bloom et al., 2018; Bachmann and Bayer, 2014), agency frictions (Arelano et al., 2019), search frictions (Leduc and Liu, 2016; Fasani and Rossi, 2018), precautionary behaviour of households (Basu and Bundick, 2017), or credit tightening (Christiano et al., 2014; Bonciani and van Roye, 2016). The magnitude of the expected output effects varies from fairly strong (e.g., Christiano et al., 2014) to fairly weak (e.g., Bachmann and

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<sup>5</sup>For a comprehensive review, see Castelnovo (2022).

Bayer, 2013), and potentially followed by a rebound (e.g., Bloom, 2009; Bloom et al., 2018). The impact of uncertainty on goods prices is even more ambiguous. Some models predict a deflationary response (e.g., Basu and Bundick, 2017; Brianti, 2021); others suggest the presence of inflationary pressures, as firms tend to increase their markups and bias their prices upward in response to uncertainty shocks in order to avoid being stuck with too low a price should a recession not materialise (e.g. Born and Pfeifer, 2014; Bonciani and van Roye, 2016; Fernández-Villaverde et al., 2015; Fasani and Rossi, 2018); while others remain inconclusive, depending, e.g., on the monetary policy rule as in Leduc and Liu (2016) versus Fasani and Rossi (2018) or on the strength of the included nominal rigidities as in Bonciani and van Roye (2016).

The empirical identification of financial and uncertainty shocks often relies on using exclusion restrictions (see footnote 3). More recently, alternative and less restrictive identifying assumptions have been proposed to estimate the causal effects of financial or uncertainty shocks in isolation. One can restrict the SVAR's forecast error variance decomposition as in, e.g., Kwon (2020); impose sign restrictions on credit spreads and estimated default probabilities (Meeks, 2012); find or construct a valid instrumental variable (Stock and Watson, 2012; Piffer and Podstawski, 2018); rely on heteroscedasticity in the shocks across different periods in order to achieve statistical identification (Angelini et al., 2019; Brunnermeier et al., 2021); or exploit shock-based restrictions (similar to AR18) and external variable constraints (Ludvigson et al., 2021).

Moreover, some precedents for the joint identification of financial and uncertainty shocks exist. Caldara et al. (2016) assume that financial and uncertainty shocks maximize the IRFs of their respective target variables; Brianti (2021) exploits the qualitatively different response of corporate cash holdings in response to financial and uncertainty shocks; Furlanetto et al. (2019) combine traditional sign restrictions on IRFs with restrictions on their ratios; and Caggiano et al. (2021) add narrative sign restrictions to a modification of the identification scheme in Furlanetto et al. (2019).

### III Framework and identification

#### III.A Data and model specification

The dynamic causal effects of financial shocks and uncertainty shocks are estimated using an SVAR. This methodology is well-established in the related literature and allows to decompose the reduced-form (dynamic) correlations into exogenous innovations and their endogenous propagation. The reduced-form VAR is given by

$$y_t = a_0 + \sum_{k=1}^K A_k y_{t-k} + B \varepsilon_t, \quad (1)$$

where  $y_t$  denotes the vector of endogenous variables,  $a_0$  is a vector of constants,  $A_k$  captures the dynamic relations (lag order  $K = 12$ ),  $\varepsilon_t$  are uncorrelated structural shocks and the impact matrix  $B$  comprises the contemporaneous responses of the variables to all shocks. The model is estimated with Bayesian techniques, using an uninformative prior.

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 excludes the Covid-19 crisis that may be subject to parameter instability.

We include real GDP, GDP deflator, the 10-year Treasury yield, the GZ corporate bond spreads and, in turn, one of the five uncertainty measures considered in this paper. All variables are shown in the Appendix. Real GDP and the GDP deflator enter the model in logs and are interpolated (e.g., Bernanke and Mihov, 1998; Uhlig, 2005). The interpolation of GDP uses industrial production and real retail sales; while the GDP deflator is interpolated using the consumer price index and the producer price index; thereby, including supply and demand considerations.

The long-term Treasury rate and corporate spreads control for financing conditions. The 10-year Treasury yield moreover captures the transmission of unconventional monetary poli-

cies (such as quantitative easing and forward guidance) via the term premium and interest rate expectations.

As for uncertainty, following the terminology in Segal et al. (2015), we employ four different uncertainty proxies for so-called “bad uncertainty”, which tend to rise if a tail risk on the downside is expected to materialise: (1) the consumer’s perceived uncertainty by Leduc and Liu (2016), (2) the US CISS by Chavleishvili and Kremer (2021), (3) the stock market volatility by Bloom (2009), and (4) the Economic Policy Uncertainty (EPU) index by Baker et al. (2016). In addition, we also use the forecast-error based macroeconomic uncertainty measure estimated by Jurado et al. (2015). In contrast to the “bad uncertainty” measures, increases in this variable can either be related to an increase in “good uncertainty” and hence be associated with higher economic growth; or to an increase in “bad uncertainty”, and therefore be associated with lower growth.<sup>6</sup>

Consumers’ perceived uncertainty is based on the Michigan consumer sentiment survey. It is constructed as the fraction of respondents reporting that it is a bad time to purchase a vehicle, because the future is uncertain. A higher index implies higher bad uncertainty about the economic outlook (see Appendix). The correlation with other uncertainty measures is positive, but relatively small: the correlation over the 1984-2019 sample period is 43.5% with CISS, 23.2% with VXO, 53.0% with EPU and 28.3% with macroeconomic uncertainty.

The US CISS is an aggregation of 15 indicators capturing financial stress, comprising money markets, bond markets, equity markets, and foreign exchange markets (see Appendix). System-wide stress is computed by weighing each pair of indicators by their time-varying correlation coefficient. This methodology allows the CISS to put relatively more weight on situations in which stress prevails in several market segments at the same time. Therefore, it captures second moments dynamics beyond the stock market volatility and it is more persistent.

EPU is based on newspaper coverage aiming at capturing uncertainty about policy-making, while the other gauges measure economic uncertainty. The CISS is positively correlated with the VXO (77.7%), EPU (33.4%) and macroeconomic uncertainty (70.7%). The VXO is positively correlated with EPU (35.0%) and macroeconomic uncertainty (55.4%)

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<sup>6</sup>Segal et al. (2015) and Rossi and Sekhposyan (2015) also propose “positive” and “negative” uncertainty indices, but focus on measures in a lower frequency data environment.

and the latter is also positively correlated with EPU (20.0%).

All in all, consumers' perceived uncertainty, based on households' intentions, and the CISS, based on the covariance of a large number of financial variables, are employed as our main alternative uncertainty gauges. The stock market volatility that is a sub-component of the CISS, EPU that focuses only on the policy-making uncertainty and the symmetric JLN macroeconomic uncertainty gauge are used as a tentative cross-check given their relevance in the literature.

All these different measures tend to rise during the NBER recessions and are positively correlated with corporate spreads (44.3% with consumers' uncertainty, 69.9% with CISS, 63.0% with VXO, 38.1% with EPU and 74.8% with macroeconomic uncertainty). Measures of risk and uncertainty are correlated because uncertainty shocks 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.

The impulse response functions (IRFs) that trace out the dynamic effects of the structural shocks  $\varepsilon_t$  can be obtained by inverting the VAR in equation (1) into a moving average process  $y_t = \phi_0 + \sum_{k=1}^{\infty} \Phi_k B \varepsilon_{t-k}$ . They are, however, not uniquely identified as any orthogonal rotation of  $B$  delivers a different MA-process that is equally consistent with the data. In the following sections, we describe how this problem is solved by combining restrictions on  $B$  (Section III.C) with narrative information in the likelihood function (Section III.B).

### III.B Restrictions on identified structural shocks

This section introduces the narrative restrictions employed to identify financial and uncertainty shocks. We rely on the approach in AR18; yet, for the financial and uncertainty shocks we do not impose any sign restrictions on the impact matrix. Instead, the identification draws entirely on two kinds of narrative restrictions; that is, sign restrictions and signed contribution restrictions. The former correspond to the “narrative sign restrictions” in AR18 and are implemented in the exact same way, while the latter are a less restrictive and more flexible adaptation of their “weak contribution restrictions”.

**Narrative sign restrictions.** As in AR18, a narrative sign restriction on a structural shock imposes that the value of the identified structural shock  $i$  on a specific date  $t$  is either

positive or negative:

$$\varepsilon_{i,t} > 0 \text{ or } \varepsilon_{i,t} < 0 \text{ at a given } t. \quad (2)$$

For example, if there is substantial evidence that an adverse uncertainty shock took place in a particular month, then we can restrict the uncertainty shock identified within our model to have a positive value on that date.

**Signed contribution restrictions.** Following AR18, we also impose, on the restricted dates, that the structural shock of interest is the most important contributor to the one-step ahead forecast error of the corresponding variable in the VAR. Differently from the original approach, however, we allow the unrestricted shocks to have an even larger contribution to the one-step ahead forecast error of the same variable if the contribution of that unrestricted shock moves the forecast error in the opposite direction of the restricted shock. Hence, our identification strategy is less restrictive than AR18's approach.

The extra flexibility derived from this modification can be of substantial importance. Consider any extreme event in the sample that is a candidate for imposing a contribution restriction. Policymakers can intervene to provide macroeconomic support in order to (partially) offset or even overturn any potential adverse macroeconomic effects ensuing from the event. The monetary policymaker in particular can immediately and abundantly provide liquidity to financial markets so that the policy stance could almost instantly become expansionary; that is, on this particular date, the policy intervention may exceed its VAR-implied Taylor-rule prescription and constitute an extraordinary accommodative monetary policy shock. This is facilitated by the signed contribution restrictions.

More precisely, 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  $B_{i,t} = \mathbb{1}((H_{i,t} \cdot \text{sign}(h_{i,t})) > 0)$  is a vector-valued indicator function. For a specific date  $t$ , we impose:

$$|h_{i,t}| > \max(\mathbb{S}(|H_{i,t}|, B_{i,t})), \quad (3)$$

while the traditional approach by AR18 imposes that  $|h_{i,t}| > \max(|H_{i,t}|)$ .

In some cases, the signed contribution restrictions also facilitate a more agnostic approach for imposing, on the same date and on one single forecast error, two different contribution restrictions. More precisely, the original approach necessitates the researcher to take a stance on which of the two restricted structural shocks is the most important, while the extra flexibility of also assigning a sign to the contribution restriction allows one shock to be the strongest contributor with a negative sign, while the other shock can be restricted to be the strongest contributor with a positive sign. In this particular case, no judgment call with respect to the relative contribution of both shocks is required. Section VII illustrates the cross-narrative restriction case.

### III.C Sign restrictions on impact responses

One could argue that the shocks of interests are not orthogonal to the traditional cost-push, demand, and interest rate shocks. Moreover, as suggested by Canova and Paustian (2011), inference related to the shocks of interest may be improved by identifying additional macroeconomic shocks, even though they are not of primary interest for the analysis. Therefore, a full model is estimated, where financial and uncertainty shocks are identified together with the standard cost-push, demand, and interest rate shocks.

Standard economic theory provides an uncontroversial set of sign restrictions that can be imposed on the impact matrix to aid identification of those traditional shocks. Specifically, we assume that adverse aggregate demand shocks are characterized by a fall in output and goods prices, a widening of credit spreads (because of the counter-cyclical risk premia), an increase in uncertainty (as the economic outlook becomes less predictable) and a fall in the 10-year Treasury yield (as economic agents expect the monetary policy maker to support the economy). For the interest rate shock, we impose the assumptions that exogenous increases in the interest rate causes goods prices to fall as in Uhlig (2005) and AR18, while corporate spreads widen in line with the findings of Caldara and Herbst (2019), Jarociński and Karadi (2020), and Brunnermeier et al. (2021). The responses of output and uncertainty are left unrestricted. Cost-push shocks are assumed to move real activity and goods prices in opposing directions. These restrictions are respectively listed in columns 3, 2, and 1 of

Table 1.

While models generally agree on the recessionary effects of both financial shocks and uncertainty shocks, we choose to leave the impact responses of all variables, including output, unrestricted for both shocks. This mimics the agnosticism maintained in Uhlig (2005) and avoids the necessity to form *a priori* a judgment regarding the sign and the timing of the propagation of the shock. As reported in columns four and five of Table 1, we only impose the normalizing restriction that uncertainty shocks increase the uncertainty variable and that financial shocks increase corporate bond spreads.

### III.D Identifying information from historical episodes

This section describes the different events in our sample that we can predominantly associate with one of the structural shocks in our model. Overall, we introduce seven signed contribution restrictions: one on the financial shock; two on the uncertainty shock; three on the interest rate shock; and one on the demand shock. In addition, four extra narrative sign restrictions are imposed: two on the financial shock and two on the uncertainty shock. They are summarized in Table 1 and Figure 1.

**Financial shocks.** The signed contribution restriction that we use to identify the financial shock relies on the risk-repricing that took place in July 2007. We impose that the financial shock in that month provides the largest positive contribution to the forecast error of US corporate spreads. In July 2007, 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 by 70 basis points relative to the previous month (Panel F), while uncertainty about the economic outlook declined in the case of consumers' uncertainty and EPU (Panels I and R), remained broadly invariant in the case of the CISS (Panel L) and marginally increased as in the case of VXO and macroeconomic uncertainty (Panels O and U). The mass downgrade was seen as a one-off intervention and ratings were expected to remain stable thereafter.

**Uncertainty shocks.** To identify the uncertainty shocks, we impose a signed contribution restriction in October 1987, following the Black Monday stock market crash, and in



August 2007, as a result of the the inter-bank liquidity crisis. Specifically, we assume that on those dates uncertainty shocks provide the largest positive contribution to the forecast error of the uncertainty indicators.

On Monday, October 19, 1987, the S&P 500 index dropped by about 20% and financial stress rose due to panic in financial markets. The immediate policy response of the FED, including moral suasion, was aimed at restoring proper market functioning. This persuaded banks to continue lending on their usual terms and possibly avoided a tightening in credit markets with the GZ spread remaining stable. The Greenbook prepared for the FOMC meeting on November 3 reports that the strains in credit markets were limited to the junk segment where *“tiering has developed since the stock market collapse; yields on lower-quality issues—those more akin to equity—have firmed while rates on the upper tier have moved a little lower.”* More importantly, the stock market crash strongly affected economic uncertainty: the Greenbook further reports that *“The effects of recent financial events become an even greater forecasting issue as one looks beyond the current quarter”* and the transcripts of the meeting reveal that the Michigan Survey of Consumers had reported that *“the big effect is not going to be wealth effect on consumer spending but the uncertainty”*.

Therefore, in line with common wisdom (e.g. Bloom, 2009; Ludvigson et al., 2021; Caggiano et al., 2021), the major developments in the unexplained component of the uncertainty gauges in October 1987 are attributed to uncertainty shocks. In that month, consumers’ uncertainty, the CISS, the VXO and EPU increased by about three times as much relative to the previous month (Panels H, K, N, Q) and macroeconomic uncertainty by about 5% (Panel T). At the same time, the Federal Reserve immediately cut the Federal Funds rate by 50 basis points and provided ample liquidity. This reduced the 10-year interest rate by about 70 basis points which can reflect an expansionary monetary policy shock in support of financial markets and the entire economy.

In August 2007, severe liquidity issues impeded the proper functioning of wholesale financial markets. The decision of BNP Paribas to freeze withdrawals from three funds that were exposed to the US subprime mortgage market created the need, but also the inability, to assess which institutions were most exposed to any potential losses accruing from securitized financial products. The shock primarily affected the wholesale repo market, where

precautionary behaviour resulted in strongly rising haircuts applied to collateral that was previously deemed safe. As shown in Ashcraft et al. (2011) and Acharya and Merrouche (2013), the liquidity hoarding had a precautionary nature, rather than being inspired by counterparty risk concerns. In support of this conclusion, corporate spreads of prime banks with AAA or AA credit ratings, some of which trade in the inter-bank market, increased on average by only 15 basis points in August 2007, while the TED spread, which represents the difference between the interest rate on three-month U.S. Treasury bills and the three-month London Interbank Offer Rate (LIBOR), rose by 120 basis points in the same month. In response to the liquidity freeze, central banks' policy measures in August 2007 were aimed at restoring the orderly functioning of wholesale funding markets and preserving a healthy flow of liquidity by acting as a lender-of-last-resort. As a result, while credit spreads of non-financial corporations rose only marginally in August (Panel F), consumers' uncertainty and the CISS increased fourfold relative to the preceding month (Panels I and L), EPU doubled (Panel R), the VXO increased by about 50% (Panel O) and macroeconomic uncertainty by about 5% (Panel U).

Finally, we sign-restrict the period around the bankruptcy of Lehman Brothers (September and October 2008) with adverse financial and uncertainty shocks. After the bankruptcy of Lehman Brothers on September 15, 2008, the GZ corporate credit spreads rose by 100 basis points in September and 370 basis points in October (Panel G). At the same time, 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 were holding more capital, became more risk-averse, and reduced lending to firms (Jermann and Quadrini, 2012; Gilchrist and Zakrajšek, 2012). Also 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., 2021). Also Caggiano et al. (2021) select these two months to identify financial and uncertainty shocks. Over these two months, all uncertainty measures reported in Figure 1 strongly rose.

**Demand shocks.** We also use a signed contribution restriction for demand shocks. This restriction imposes that among the shocks that contributed positively to the forecast error for

**Table 1:** Sign and narrative restrictions

	Supply	Interest rate	Demand	Financial	Uncertainty
Variables	<i>Sign restrictions on the impact matrix</i>				
Real GDP	+		-		
Goods prices	-	-	-		
Interest rate		+	-		
GZ credit spreads		+	+	+	
Uncertainty			+		+
Dates	<i>narrative sign restrictions and contribution restrictions</i>				
02/1994		Interest rate ↑↑			
03/2009, 09/2013		Interest rate ↓↓			
01/2006			GDP ↑↑		
07/2007				Credit spreads ↑↑	
10/1987, 08/2007					Uncertainty ↑↑
Dates	<i>Sign narrative restrictions only</i>				
09/2008, 10/2008				Credit spreads ↑	Uncertainty ↑

GDP in January 2006, demand shocks are the strongest (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 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 than we had earlier thought*”. Given that real retail sales grew at an annual rate of 26.9% in January 2006 and that consumer price index (CPI) and producer price index (PPI) rose by about an annualized 7% in the same month with upward implications for the GDP deflator (Panel B), we relate this forecast error predominantly to a favourable demand shock.<sup>7</sup>

**Interest rate shocks.** The identification scheme for the interest rate shocks is complemented with three signed contribution restrictions that come from relatively well-understood monetary policy shocks that via the Treasury yield curve affect our interest rate variable. First, we impose a signed contribution restriction in February 1994 to identify an exogenous rise in interest rates due to a contractionary monetary policy shock as in AR18, which contributed to the observed 60-basis point rise in the 10-year Treasury rate (Panel C). AR18 classify this event as of particular interest, as it was not shaped by a forthcoming recession,

<sup>7</sup>The results are robust to excluding the signed contribution restriction used to identify the demand shocks (see Appendix).

given that output accelerated during 1994.

The second signed contribution restriction used for the interest rate shock corresponds to the expansionary monetary policy shift in March 2009 (Panel D). Swanson (2020) shows that the “QE1” announcement of the “large-scale asset purchases” (LSAPs) at the zero lower bound constituted an extraordinary shock for long-term interest rates on March 18, 2009, which surprised financial markets. In our monthly dataset, the 10-year Treasury rate declined by 55 basis points in March 2009 relative to the previous month (Panel D).

Finally, we also use an episode during the so-called “taper tantrum” in 2013. 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. The prospect of a reduction in the rate of the FED’s asset purchases changed investor expectations, who responded immediately by selling bonds and pushing up 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 tapering was imminent, and interest rates rose further by 40 basis points in the following months. Overall, between May and August 2013, the 10-year Treasury rate 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 an exogenous tightening shock (see discussion in Section VI). However, the FOMC surprised the markets in September 2013 by not tapering and the 10-year Treasury rate declined by 15 basis points in that month (Panel E). Swanson (2020) quantifies this latter decision as the second largest LSAP shock in his sample.

## **IV Business cycle response to economic shocks**

### **IV.A Recursive identification**

We start our analysis with four variables and the recursive identification approach often used in the literature with the uncertainty gauge being ordered either first or last in the VAR, and credit spreads left out from the model. We replicate recurring results documented in the literature; that is, an uncertainty shock sharply reduces output, particularly if the uncertainty measure is ordered first. The results on goods prices depend on the type of

uncertainty measure used and the order of the variables in the VAR (first and second rows on the right side of Figure 2). In general, goods prices tend to decline.

We also run the analysis excluding uncertainty while including credit spreads to identify financial shocks in a recursive ordering. We replicate the results in the literature, which suggest a sharp decline in output and goods prices after a financial shock regardless of the ordering of the variable (first and second rows on the left side of Figure 2).

## IV.B Partial identified SVAR with narrative restriction

Next, we estimate the five variable model and identify the financial and the uncertainty shocks jointly, by employing only the narrative restrictions described in last two columns of Table 1, using either AR18's contribution restriction  $|h_{i,t}| > \max(|H_{i,t}|)$  (third row) or the signed contribution restriction  $|h_{i,t}| > \max(\$(|H_{i,t}|, B_{it}))$  (fourth row). Notice that usually the narrative restrictions are used to narrow down the identified set obtained with sign restrictions. Here, instead, we do not impose sign restrictions on the impact matrix, except for a normalization of the sign of the shocks. The response of all variables is fully determined by the data, also at impact.

The results, which are broadly the same across the two sets of models, suggest that output and goods prices decline in response to financial shocks, while output contracts and goods prices are unresponsive after uncertainty shocks (i.e. the 68% credible set includes zero), as in Caggiano et al. (2021). The responses of GDP and prices to financial shocks are independent of the type of uncertainty measure employed, except that using macroeconomic uncertainty reduces the persistence of the response. Also the responses of GDP to uncertainty shocks are broadly similar across the various uncertainty measures, except when using VXO, as the output effect is much smaller.

All in all, we can disentangle financial shocks and uncertainty shocks by only imposing a few narrative restrictions. This suggests that narrative restrictions work on their own without the need to restrict the impact matrix or IRFs. This feature is particularly useful if the responses of the restricted variables to different shocks have the same sign or if economic theory disagrees on the transmission mechanism of a specific shock. Both situations apply to the case in question: disentangling financial versus uncertainty shocks.

## IV.C Fully identified SVAR with narrative restrictions

Partially identified SVARs may contain a large amount of identification uncertainty which can be reduced by identifying additional shocks (Canova and Paustian, 2011). Therefore, we turn to the results where financial and uncertainty shocks are identified alongside interest rate, demand, and cost-push shocks. Narrative restrictions to identify financial and uncertainty shocks are complemented with sign restrictions and other narrative restrictions to identify the other three shocks. All restrictions are listed in Table 1.<sup>8</sup>

Figure 3 shows the distribution of shocks in some specific periods, useful to identify the demand shocks (January 2006), the financial shocks (July 2007) and the monetary policy shocks (September 2013), using the full (blue) and partial (red) identification. By identifying the other shocks, the model recognizes that financial shocks were mostly positive in September 2013, when the FED achieved monetary accommodation. Similar conclusions can be drawn in January 2006, when output and goods prices rose due to demand factors, which imply, if identified, stronger financial shocks in the same month. Some differences also emerge in months when the narrative restriction is introduced in both models. The fully identified model suggests that uncertainty shocks were more adverse in July 2007 relative to a partially identified model. The distribution of the uncertainty and financial shocks of the partially versus fully identified model can be considerably different and this can have an effect on the response of the variables.

IRFs obtained with the fully identified model are shown in Figure 4, where we provide the full set of IRFs associated to all five identified shocks using our preferred uncertainty measures: consumers' uncertainty (blue) and the CISS (red). They respectively rely on consumers' intentions and a broad coverage of financial markets.

The responses to financial shocks are qualitatively similar to demand shocks: they decrease output, goods prices and interest rates, and increase corporate spreads and uncertainty. Differences emerge with regard to the size and the persistence of the responses.

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<sup>8</sup>The unidentified impulse responses following from the sign restrictions only, described in Table 1, are illustrated in Figure A1 of the Appendix. This set of restrictions is not sufficient to disentangle any of the structural shocks from the reduced-form innovations. For example, even the demand shock, which in our identification scheme has the maximum amount of impact restrictions possible, is not identified: economic theory cannot exclude the possibility that either the financial shock or the uncertainty shock have the same signs in the impact matrix as the signs imposed for the demand shock (or for any of the other shocks).

Adverse demand shocks generate an immediate and persistent contraction on output and goods prices, while financial shocks generate a larger contraction in output and prices only after about one year. At the same time, the immediate impact on interest rates is smaller in the case of financial shocks. In response to uncertainty shocks, the negative response of output is even more prolonged than for financial shocks, while goods prices increase. In line with the persistent effect shown in Bachmann and Bayer (2013), there is no evidence of an overshooting pattern of output in response to uncertainty shocks, which suggests the limited importance of wait-and-see business cycles (Bloom, 2009) in the aggregate data.

The results suggest that interest rate conditions are an important part of the mechanism through which financial and uncertainty shocks affect the macroeconomy. The decline in interest rates that follows a financial shock attenuates the negative impact on output. Conversely, in response to uncertainty shocks, interest rates may not react or may even increase in response to inflationary pressures and, as a result, prolong the fall in output.

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 an increase in corporate spreads in line with the results obtained by Caggiano et al. (2021) and Christiano et al. (2014). These positive spillovers between corporate spreads and uncertainty amplify the effects of financial and uncertainty shocks.

Financial shocks explain the largest portion of the Forecast Error Variance Decomposition (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 gauge (see Appendix). This outcome corroborates the intuition of Caldara et al. (2016); although, their portion of the FEVD attributable to financial and uncertainty shocks is somewhat larger, in line with their identifying assumptions. The results also suggest that financial shocks tend to have a relatively higher economic importance on GDP after 1 year, while uncertainty shocks are more important after about 3 years, particularly if the CISS measure is used. Uncertainty shocks play a bigger role than financial shocks in the dynamics of prices in the short term. Overall, the results suggest that both shocks are important drivers of the business cycles in the US.

The key result that uncertainty shocks are inflationary holds also when using industrial production as a measure of output (see Figure 5). The impact of financial shocks on prices, moreover, remains deflationary, yet less clearly so when using the consumers' perceived uncertainty. As industrial production accounts only for a small fraction of output in the US, real GDP is considered to be a better indicator of broader macroeconomic conditions and the IRFs obtained by using GDP rather than industrial production are more easy to interpret and more useful for policy-making (Bernanke and Mihov, 1995). Consequently, we continue the analysis using the interpolated variables. The method of interpolation does not affect the results: the deflationary financial shocks and inflationary uncertainty shocks emerge irrespective of using Chow and Lin (1971)'s interpolation, which is robust to first-order serial autocorrelation in the monthly error terms, used in monetary VARs since Bernanke and Mihov (1995); or using the Litterman (1983) procedure, which accounts for more general forms of autocorrelation and facilitates the use of non-stationary data (see Figure 5).

More importantly, we also show that the estimated responses of financial and uncertainty shocks are broadly similar when using the other uncertainty measures (EPU, VXO, and JLN's macroeconomic uncertainty, see Figure 6). Using macroeconomic uncertainty, however, tends to mitigate the deflationary effect of financial shocks, while EPU and VXO somewhat reduce the contractionary effects of adverse uncertainty shocks. The significance of these responses is, however, magnified when the increased uncertainty following the terrorist attacks of 9/11 is added to the set of signed contribution restrictions (see Section VIII). The responses of all variables to the other three identified shocks (demand, cost-push and interest rate shocks) are very similar to the benchmark results in Figure 4 and the complete set of results is provided in the Appendix.

It is worth to point out that the correlations between the shocks identified with our model and the corresponding shocks identified using a recursiveness assumption are positive and close to 70%.<sup>9</sup>

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<sup>9</sup>A set of correlation coefficients is computed by pairing the point-identified shock series from the recursive model with each draw of the structural shocks' time series in the identified set. The median of that set of correlation coefficients for the financial shock, if corporate spreads are ordered first (last), is 74% (71%) with consumers' perceived uncertainty, 72% (69%) with CISS, 75% (70%) with EPU, 71% (70%) with VXO, and 71% (72%) with macroeconomic uncertainty. The median of that set of correlation coefficients for the uncertainty shock, if the uncertainty measures are ordered first (last), is 74% (74%) with consumers' perceived uncertainty, 71% (70%) with CISS, 73% (74%) with EPU, 71% (70%) with VXO, and 71% (72%) with macroeconomic uncertainty.



At the same time, the variance of GDP and GDP deflator explained by the recursive shocks is only a tiny fraction. In the case of the two-year horizon for GDP and shocks ordered recursively first, the FEVD explained by financial shocks is below 7% and the FEVD explained by uncertainty shocks is below 3% for the consumers' perceived uncertainty and the VXO, below 4% for the CISS and the EPU, and less than 7% for the macroeconomic uncertainty. The fraction of the GDP deflator is about halved that of real GDP. In contrast, the FEVD of real GDP explained by financial shocks with our model can reach 40% in the case of consumer perceived uncertainty and 10% in the case of the CISS; while the FEVD of real GDP explained by uncertainty shocks can reach 25% in the case of both measures. The fraction of the GDP deflator explained by financial and uncertainty shocks is about 10% and 5%, respectively (see Appendix).

#### IV.D Response of price markups and savings rate

The negative impact of financial shocks on goods prices is more in line with a transmission mechanism via aggregate demand where consumption and investment are intertemporally reallocated (e.g. Smets and Wouters, 2007; Del Negro et al., 2015; Ajello, 2016), rather than through a direct positive impact on firms' marginal costs (e.g. Christiano et al., 2015) or pricing decisions (e.g. Gilchrist et al., 2017). The positive response of goods prices to uncertainty shocks, instead, is in line with the upward pricing bias put forward in, e.g., Born and Pfeifer (2014), Bonciani and van Roye (2016), Fasani and Rossi (2018), where firms tend to increase their markups in response to uncertainty shocks to avoid being stuck with too low a price.

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.<sup>10</sup> In particular, we estimate their response by local projections (Jorda, 2005), as described in equation (4), where  $y_t^j$  is either one of the two preferred quarterly price markup measures,  $\epsilon_t^i$  is the quarterly average of either the financial shock or the uncertainty shock identified in

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<sup>10</sup>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.

our SVARs, and the lag length is set to  $p = 4$ :

$$y_{t+h}^j = c_h^j + \beta_h^{i,j} \varepsilon_t^i + \sum_{l=1}^p \gamma_{h,l}^i y_{t-l}^i + u_{t+h}^j. \quad (4)$$

The coefficients  $\beta_h^{i,j}$  trace out the dynamic response of markup series  $j$  to shock  $i$  over horizons  $h = 0, \dots, 20$  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. This is achieved 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 distributions (normally distributed with Eicker-  
Huber-White standard errors Montiel Olea and Plagborg-Møller (2021)). 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 results, displayed by the shaded area in Figure 7, 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). Offsetting factors related to firm heterogeneity may explain the unclear response of aggregate markups after a financial shock, as smaller and illiquid firms tend to be counter-cyclical, while larger and more liquid firms tend to be pro-cyclical (Burstein et al., 2020; Meinen and Soares, 2022).

These results are corroborated and slightly stronger in the case of VXO and macroeconomic uncertainty, when excluding the narrative on aggregate demand (see Appendix).

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 using the savings rate as dependent variable. The time series is monthly and the lag length is set to  $p = 12$ . The results, also shown in Figure 7, confirm that the savings rate tends to increase after an uncertainty shock, while being

broadly unaffected by financial shocks.

In sum, uncertainty shocks have an inflationary impact via increased price 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.

## V Goods' price drivers during recessions

According to the National Bureau of Economic Research (NBER), the US economy in our sample was in recession between July 1990 and March 1991 due to the savings-and-loan crisis, between March and November 2001 due to the dot-com bubble, and between December 2007 and June 2009 due to the housing bubble resulting in the Global Financial Crisis (GFC). These three recessions are associated to financial markets and, therefore, they are very useful time periods to quantify the contribution of financial and uncertainty shocks in explaining the historically observed fluctuations in goods prices.

Goods prices tended to rise at the onset of these three recessions and the overall price decline during the GFC is marginal relative to the recorded drop in output. A historical decomposition of goods prices in our SVARs can shed light on the economic forces that shape price developments during recessions within our models. Figure 8 shows the historical decomposition of prices for the five SVARs, each using a different uncertainty measure. The decomposition of output is provided in the Appendix. The five different uncertainty shocks contributed positively to the price dynamics in 12 out of 15 cases, particularly at the onset of the recession in line with the upward pricing bias.

**Savings-and-loan crisis.** The Savings-and-loan crisis was a financial disaster resulting in the failure of many savings and loan associations in the US 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 uncertainty shocks measured with all five uncertainty measures as well as cost-push shocks contributed to an increase in goods prices in this recession.

**Dot-com bubble.** The 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, uncertainty shocks contributed positively to the initial increase in goods prices with all uncertainty gauges, except EPU, as well as to the price dynamics in the subsequent months, except when using CISS. In the latter case, cost-push shocks counteracted the disinflation process. The role of uncertainty shocks in this recession became even more prominent after the 9/11 attacks.

**Global Financial Crisis.** During the GFC, tightened credit conditions and increased financial stress reinforced each other, private 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 the GFC was much slower than the recoveries from recessions that were not associated with a financial crisis. The historical decomposition of the price dynamics over this period suggests that adverse financial shocks reduced goods prices, in contrast to the results of Gilchrist et al. (2017), while adverse uncertainty shocks increased prices over the entire recession period when using the consumers' perceived uncertainty, the CISS or macroeconomic uncertainty. Beyond these opposing forces, the observed fall in goods prices is attributed to interest rate shocks. After the collapse of Lehman Brothers, the Federal Reserve rapidly lowered the Federal Funds rate to zero to stimulate the economy. Yet, the 10-year US Treasury rate declined by only 130 basis points between September 2008 and March 2009 and this is interpreted by the model as monetary policy tightening. Lindé et al. (2016) and Fratto and Uhlig (2020) required large offsetting positive price markup shocks to cope with the disinflation puzzle in the Smets and Wouters (2007) setting. This is consistent with our empirical results where uncertainty shocks rise price markups. Yet, the uncertainty and cost-push shocks estimated in our model are of a much smaller magnitude, relative to those required by Lindé et al. (2016) and Fratto and Uhlig (2020).

## VI A shock narrative during the taper tantrum

Apart from disentangling the drivers of recessions, through the lenses of our model, we can also look at the economic forces at play during key economic events in our sample. In the Appendix, we ask our model what the structural shocks are that constituted the collapse of the Long Term Capital Management (LTCM) in 1998, the September 11 terrorist attacks in 2001, the 2011 debt ceiling crisis and the taper tantrum in 2013. Of particular interest is the taper tantrum, a reactionary panic to perceived US Federal Reserve hawkishness that triggered a sudden spike in bond yields.

In May 2013, (now former) FED Chair Ben Bernanke said at a congressional hearing that the Fed would, if it saw continued improvement in economic conditions, “take a step down in our pace of purchases”. After this announcement, the 10-year US Treasury increased by 120 basis points between May and August 2013. The conduct of monetary policy was dependent on incoming data, but markets interpreted this as a signal that tapering was imminent.

Based on data availability at that time up to the first quarter of 2013, the US real economy was expanding, goods inflation was rising and financial conditions were improving. Therefore, 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 computing the contribution of the shocks to the variability of the 10-year Treasury rate over the period.

At the time when the announcement was made, real macroeconomic data up to the first quarter of 2013 were available. Our model suggests that positive demand shocks characterized the US economy in the first quarter of 2013 (see Appendix), which however turned negative in April and May 2013 due to the fall in both retail sales and industrial production in April. 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 (see Appendix) in line with Swanson (2020)’s results. Hence, positive macroeconomic developments in the first quarter of 2013 and a surprisingly hawkish communication by the FED in May 2013 triggered the sharp rise in interest rates during the tapering tantrum period.

To better understand the drivers of the FED communication at that time, we compute the cumulative effects of the structural shocks on each variable, as they depend on the size

of the shocks as well as the transmission mechanism. The historical decomposition suggests that the spike in the 10-year Treasury rate between May and August 2013 is mostly due to interest rate shocks, regardless of the uncertainty gauge used (see Figure 9). Conversely, the dynamics of output, credit spreads and uncertainty are mostly driven by favourable uncertainty shocks. The latter shocks offset the negative effects the increase in long-term Treasuries.

Overall, the results of our model suggest that the FED saw a genuine continued improvement in economic conditions; but the FED communication was too hawkish causing a sudden spike in bond yields. Yet, the underlying macroeconomic forces, interpreted by the model as favourable uncertainty shocks, were so strong that the interest rate shocks did not cause real economic consequences on the US economy.

## VII Cross-narrative restriction

The modification of the AR18's identification method allows one to impose cross-narrative restriction, which may be helpful in some cases. An illustration is provided in Figure 10. The exogenous increase in uncertainty following the financial market distress in October 1987 spurred an extraordinary monetary policy response that, to the extent that the policy easing extended beyond the Taylor-rule prescription estimated in the SVAR, would qualify as a very expansionary monetary policy shock.

Assume that this episode can indeed be treated as a monetary policy expansion. This hypothesis can be implemented using either the AR18's identification scheme, which is labeled by the same authors as “weak”, or using our signed contribution restriction, by imposing that the interest rate's forecast error in that specific month is attributed to an expansionary monetary policy shock, while at the same time the uncertainty shock contributes positively and to the largest extent to the unpredicted rise of the uncertainty gauge.

However, beyond the transmission channel of monetary policy, policy makers in October 1987 also aimed at mitigating uncertainty and restoring confidence. This additional assumption can be implemented jointly only with the signed contribution restriction, by assuming that the expansionary monetary policy is also the largest contributor among all potential

drivers, if any, that reduced uncertainty in the same month, thereby containing the crisis (i.e. cross-narrative restriction). Our variation does allow other shocks (i.e. monetary policy shock) to have a larger contribution to the forecast error of the selected variable (i.e. uncertainty gauge) than the restricted shock (i.e. uncertainty shock) at the same time, provided that the contribution of the other shock goes into the opposite direction. With our modification we allow the monetary policy shock to contribute to the unforecastable component of uncertainty and avoid imposing a bound on its potential size.

The results described in Figure 10 suggest that the posterior density of the interest rate shocks in October 1987 is shifted more to the right in the case of the sign contribution restriction (see Panel A), because in this case expansionary monetary policy mitigates more strongly the uncertainty gauges (see shaded IRFs in Panel B) and, hence, a lower intervention by the policy maker is required to mitigate the crisis. It is worth noticing that we do not impose a sign restriction on the impact response of the uncertainty gauge to monetary policy shocks. The positive response at impact is endogenously determined, as a result of the cross-narrative restriction.

## VIII Robustness

A variety of robustness checks corroborate the results of the paper. We show that 9/11 2001 a suitable event to identify uncertainty shocks (see also Bloom, 2009). The results obtained using this additional narrative are presented in Figure 11 and are similar to those in Figures 4 and 6. The first two columns show the impact on GDP and prices when adding 9/11 as an extra narrative restriction, while the last two columns use 9/11 instead of Black Monday. Most notably, the impact on GDP is somewhat magnified when using VXO and EPU.

The results are also independent of the narrative restriction used for the demand shocks. The only response that is materially affected is the response of GDP to demand shocks, as the narrative restrictions narrow the 68% credible sets bands by reducing the identification uncertainty (see Appendix).

We use the GZ corporate credit spreads to capture tightness in business financing as in, e.g., Brunnermeier et al. (2021); while Caldara et al. (2016) and Caggiano et al. (2021)

use the excess bond premium, obtained by subtracting an estimated default risk premium from the GZ credit spreads. We employ the GZ spreads for two main reasons: first, Caldara and Herbst (2019) document that the monetary policy rule reacts systematically to changes in corporate credit spreads; and second, the default risk is computed using asset volatility, which in turn, may depend on uncertainty shocks. Our results are, however, very similar when the excess bond premium is used. The only responses that are materially affected are the responses of prices to uncertainty shocks when using CISS and VXO, as zero is included in the 68% credible set (see Appendix).

In line with the last two rows of Figure 2, the Appendix further illustrates the robustness of our results to using the original weak contribution restrictions of AR18 instead of the signed contribution restrictions (see Appendix).

The same conclusions follow from excluding the GZ credit spreads from the model so that financial shocks are not identified. Also in this case, uncertainty shocks reduce output and increase goods prices. Yet, controlling for financial shocks strengthens the effect of uncertainty shocks on output using consumers' uncertainty and EPU; while goods prices rise more when using CISS, VXO and macroeconomic uncertainty. Excluding the uncertainty gauge from the model and leaving uncertainty shocks unidentified also leaves our main findings intact. Yet, controlling for uncertainty makes the median impact of financial shocks on goods prices more positive (see Appendix).

Finally, the results of this paper are robust to substituting the flat prior with the Minnesota prior or the sum-of-coefficients prior (see Appendix).

## **IX Conclusions**

Using a variety of uncertainty measures suggested by the literature, we find that financial shocks are deflationary, while uncertainty shocks reduce output but tend to increase goods prices. These empirical findings complement the literature on both financial and uncertainty shocks, where models either have conflicting predictions with respect to the price response following either shock, or do not have a clear implication for prices at all. Our results suggest that in response to uncertainty shocks, firms increase their markups, in line with the upward



pricing bias in order to self-insure against being stuck with too low a price, while households tend to increase their savings rate as a hedge for income risk.

In contrast to models developed after the Great Recession that stress a potential inflationary effect of financial shocks (e.g. Gilchrist et al., 2017), we find that the demand-side transmission dominates in the aggregate data. Our results are consistent with the findings of Lindé et al. (2016) and Fratto and Uhlig (2020), who attribute an important role to price markup shocks to explain the disinflation puzzle during the GFC, because our model suggests that adverse uncertainty shocks increased price markups at the time.

Our findings do not predict an overshooting pattern of output in response to uncertainty shocks detected by Bloom (2009) in the the medium term. There is no evidence of a boom and bust cycle. The decline in production after an uncertainty shock is very persistent, as in Bachmann et al. (2013). Finally, in line with Christiano et al. (2014), credit spreads are an important part of the transmission mechanism of uncertainty shocks.

These results are obtained jointly identifying financial and uncertainty shocks without imposing any assumptions on the impact matrix using narrative restrictions. We modify the identification à la AR18, as, 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. Thereby, our proposed approach is less restrictive than AR18's method. We also find that macroeconomic uncertainty is partly an endogenous response to demand and financial shocks. Hence, the typical approach in the literature of employing the Cholesky identification method to identify uncertainty shocks is invalidated.

Lastly, we show the appeal of identifying financial and uncertainty shocks along with other standard shocks. A large part of the literature on financial 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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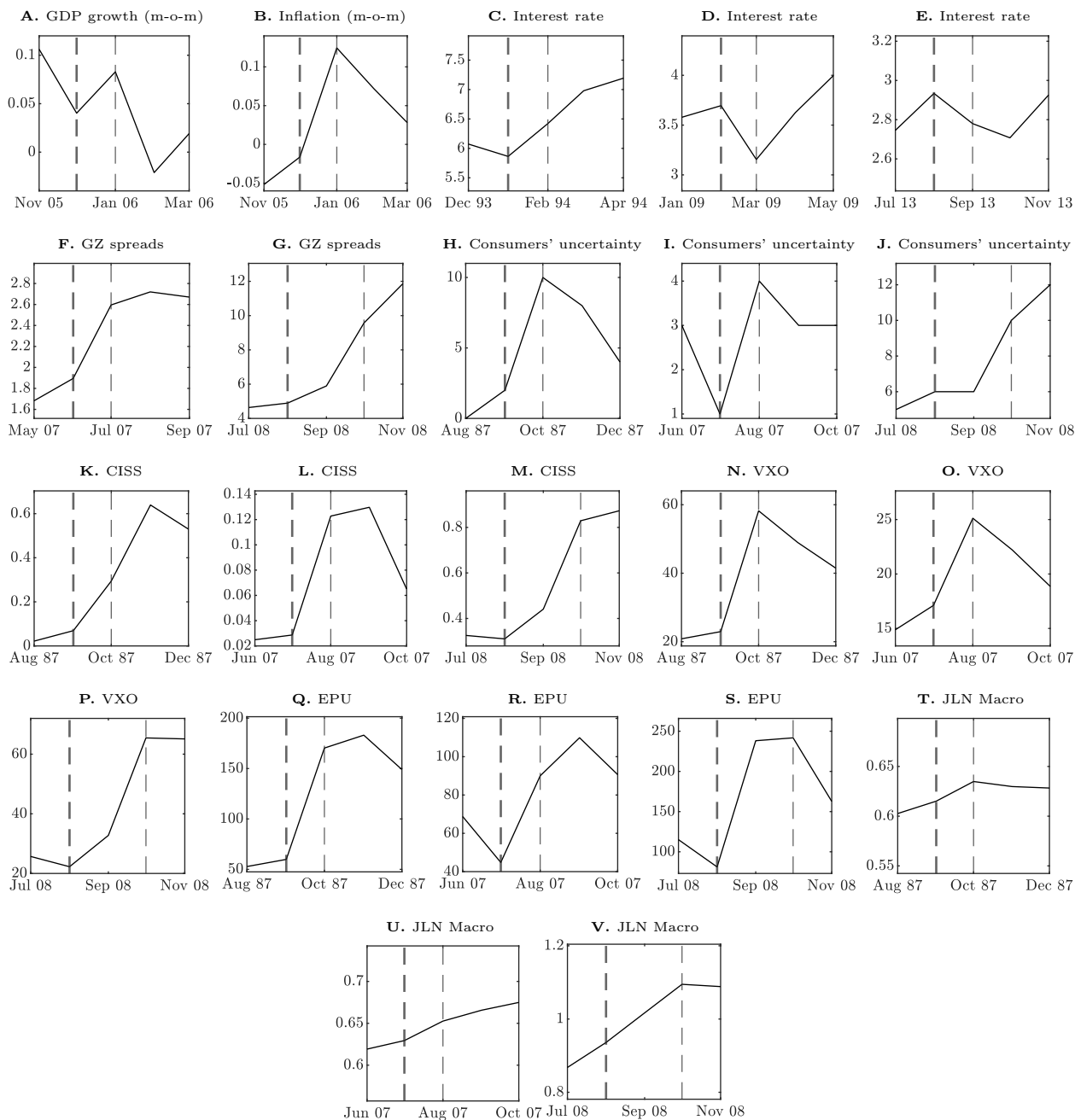
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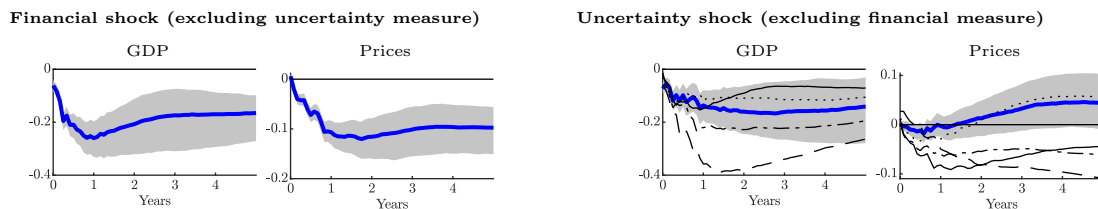
**Figure 1: Events and Narrative Restrictions**



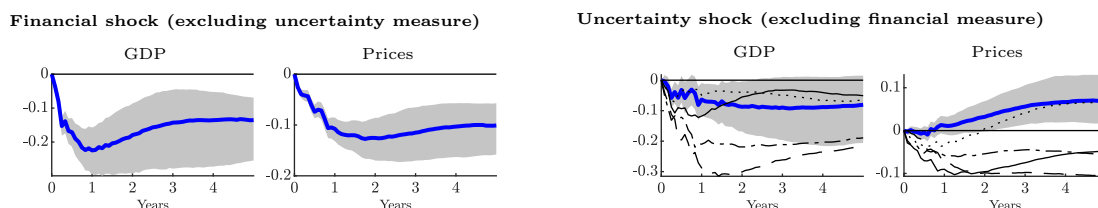
*Notes:* The two dashed lines delineate the periods over which the narrative restrictions are imposed. GDP growth (m-o-m) and inflation (m-o-m) are measured as the month-on-month percent log-difference in real GDP and GDP deflator.

**Figure 2:** Standard Identification Schemes in the Literature

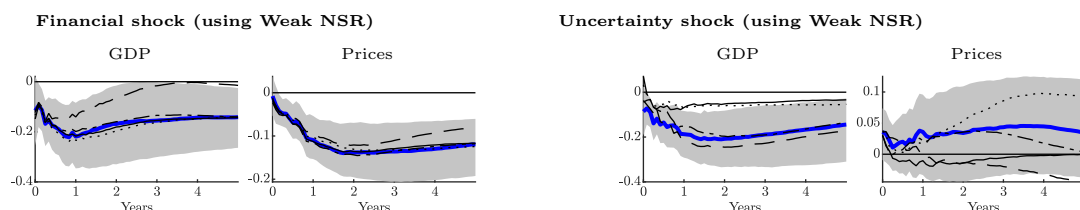
*4-Variable Cholesky (depicted shock ordered first):*



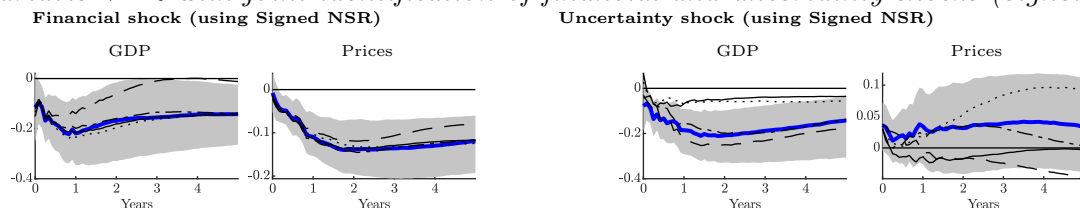
*4-Variable Cholesky (depicted shock ordered last):*



*5-Variable VAR with joint identification of financial and uncertainty shocks (weak NSRs):*



*5-Variable VAR with joint identification of financial and uncertainty shocks (signed NSRs):*

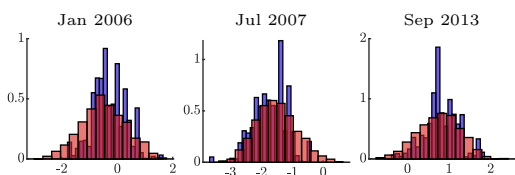


*Notes:* The first two rows show the responses of output and prices (median IRF and the 16th and 84th percentiles of the posterior distribution are represented by the blue line and shaded area) obtained from four-variable VARs that include GDP, goods prices, 10-year US Treasury rate and either GZ credit spreads (two leftmost panels) or consumers' uncertainty (two rightmost panels). In addition, on the right, the full line, dashed line, dash-dotted line and the dotted line respectively show the median IRFs obtained by replacing consumers' uncertainty with either VXO, JLN macroeconomic uncertainty, CISS, or EPU. The final two rows show the responses of output and prices (the median IRF and the 16th and 84th percentiles of the posterior distribution are represented by the blue line and shaded area) obtained from five-variable VARs that include include GDP, goods prices, 10-year US Treasury rate, GZ credit spreads and consumers' uncertainty. In addition, the full line, dashed line, dash-dotted line and the dotted line respectively show the median IRFs obtained by replacing consumers' uncertainty with either VXO, JLN macroeconomic uncertainty, CISS, or EPU. The “weak NSRs” refers to the weak contribution restrictions imposed in Antolín-Díaz and Rubio-Ramírez (2018); while the “signed NSRs” refers to the restriction as described in equation (4).

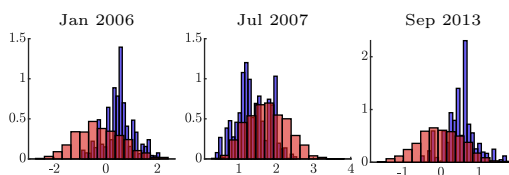
**Figure 3:** Histograms of Identified Shocks: partial Identification vs. full Identification

*Using Consumers' Uncertainty:*

**Uncertainty shock**

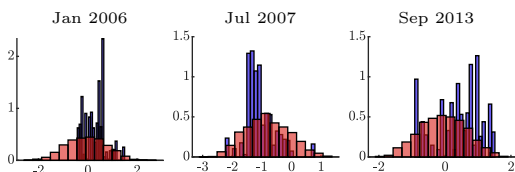


**Financial shock**

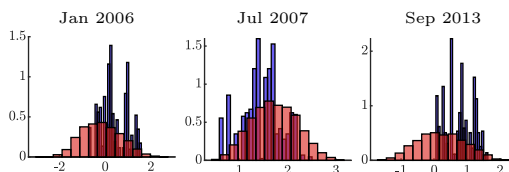


*Using CISS:*

**Uncertainty shock**

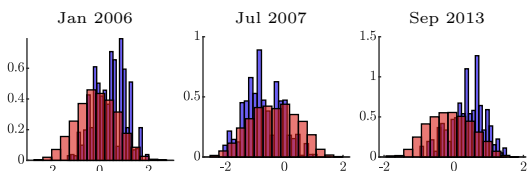


**Financial shock**

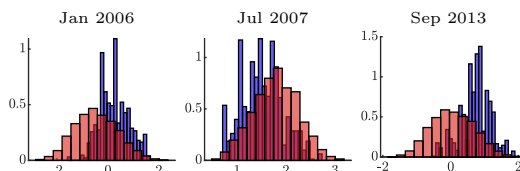


*Using VXO:*

**Uncertainty shock**

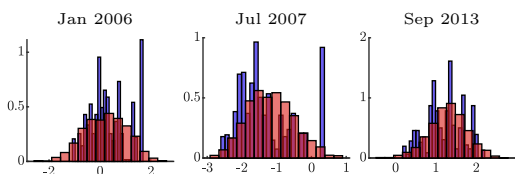


**Financial shock**

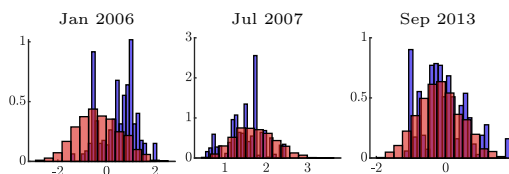


*Using EPU:*

**Uncertainty shock**

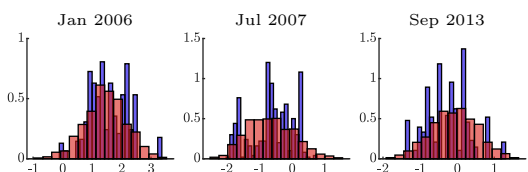


**Financial shock**

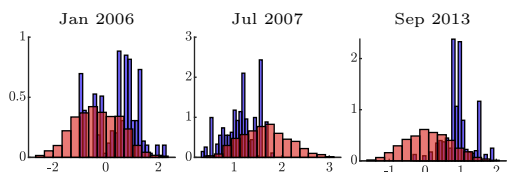


*Using JLN's Macroeconomic Uncertainty:*

**Uncertainty shock**



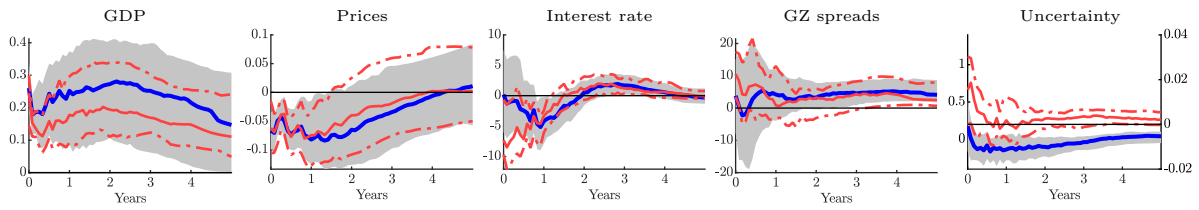
**Financial shock**



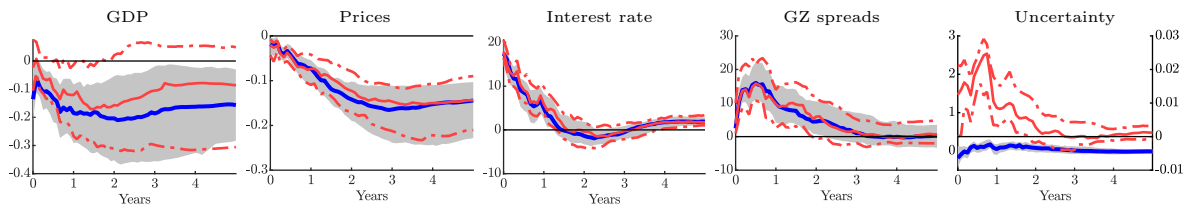
*Notes:* The represented SVARs contain five variables: GDP, goods prices, 10-year US Treasury rate, GZ credit spreads and an uncertainty variable. The histograms show the posterior density of either the uncertainty shock (three left-most columns) or the financial shock (three right-most columns). The thin histograms in blue, show the densities of the shocks identified using the restrictions listed in Table 1, while the broader histograms in red show the densities of the shocks identified using only the narrative restrictions used for the financial and uncertainty shocks. These results are obtained using the original implementation of the narrative sign restrictions as in Antolín-Díaz and Rubio-Ramírez (2018).

**Figure 4:** Responses to Shocks using Consumers' Uncertainty and CISS

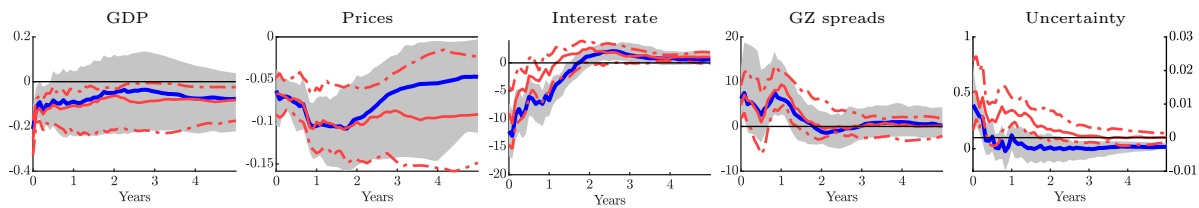
*Supply / cost-push shocks:*



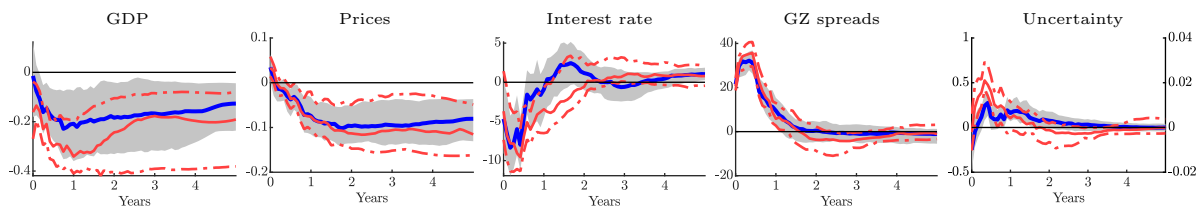
*Interest rate shocks:*



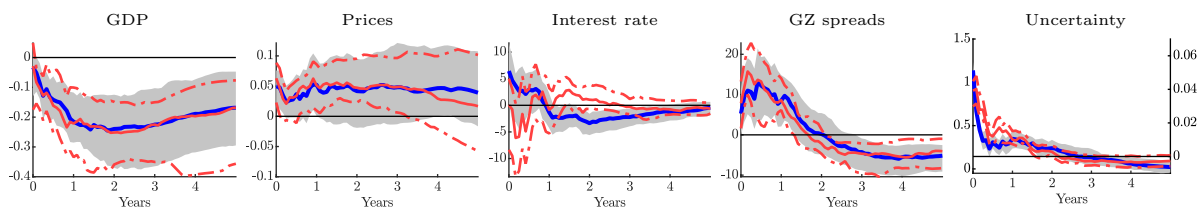
*Demand shocks:*



*Financial shocks:*



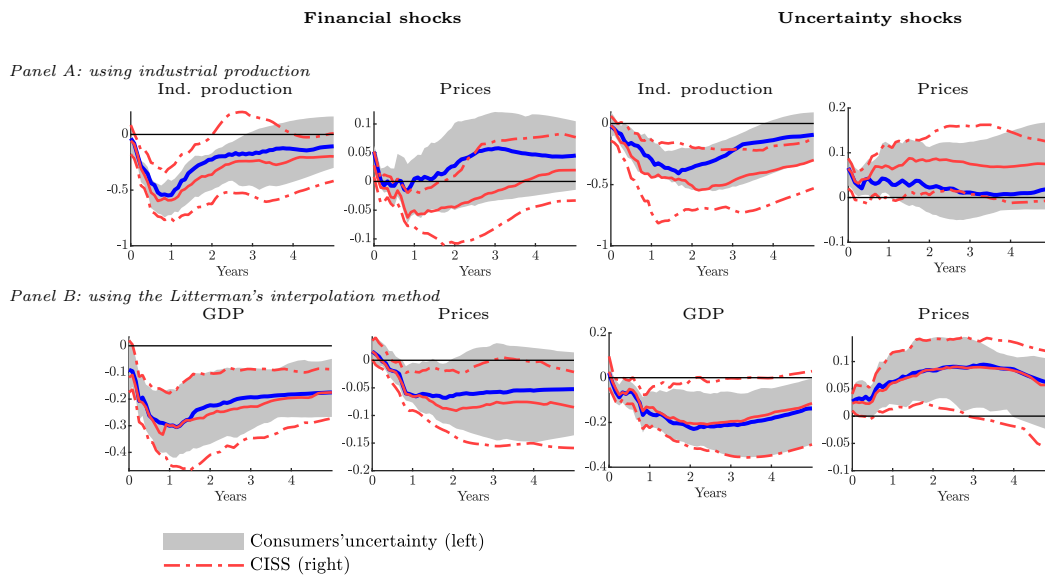
*Uncertainty shocks:*



Consumers' uncertainty (left)  
 CISS (right)

*Notes:* The represented SVARs contain five variables: GDP, goods prices, 10-year US Treasury rate, GZ credit spreads and either consumers' uncertainty or CISS. The identifying assumptions are collected in Table 1. Each panel shows the median IRFs and the corresponding posterior 68% credible sets (dashed red lines and shaded areas). The results excluding the narrative restriction for demand are similar and available in the Appendix.

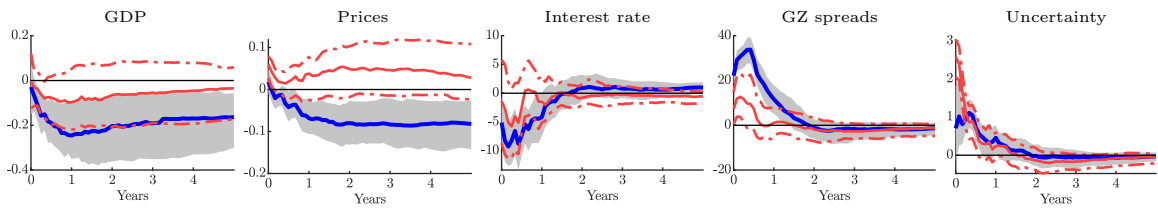
**Figure 5:** Responses to Financial and Uncertainty Shocks using alternative variables or methods



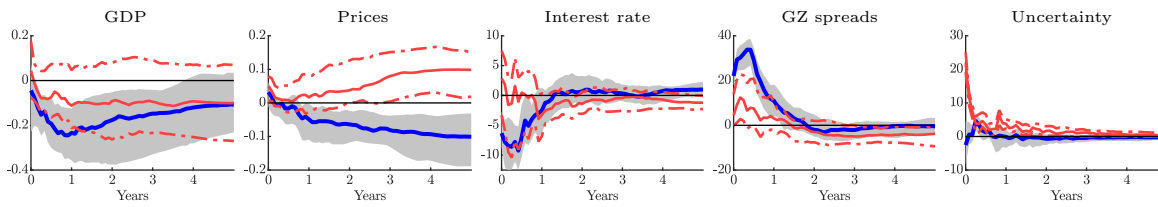
*Notes:* The represented SVARs contain five variables: Industrial production (Panel A) or GDP (Panel B), goods prices, 10-year US Treasury rate, GZ credit spreads and either consumers' uncertainty or CISS. The identifying assumptions are collected in Table 1. Each panel shows the median IRFs and the corresponding posterior 68% credible sets (dashed red lines and shaded areas). Panel B uses real GDP and GDP deflator interpolated using the Litterman (1983) procedure.

**Figure 6:** Responses to Financial and Uncertainty Shocks using Alternative Gauges

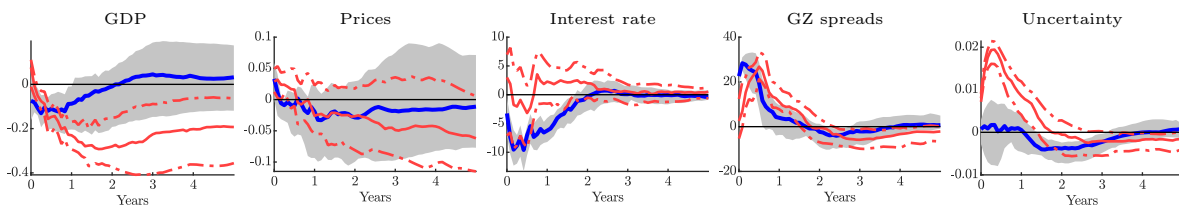
*VXO:*



*EPU:*



*JLN's Macroeconomic Uncertainty:*

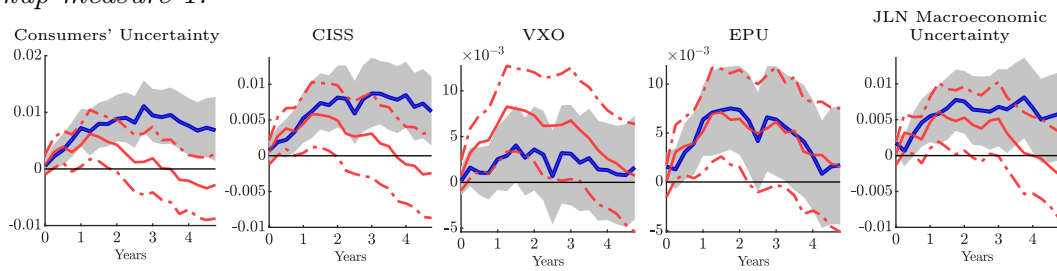


Financial shock  
 Uncertainty shock

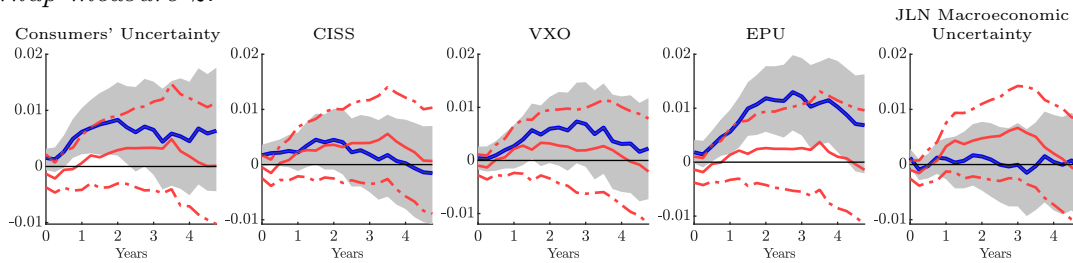
*Notes:* The represented SVARs contain five variables: GDP, goods prices, 10-year US Treasury rate, GZ credit spreads using either VOX, or EPU or macroeconomic uncertainty. The identifying assumptions are collected in Table 1. Each panel shows the median IRFs and the corresponding posterior 68% credible sets for the financial shock (shaded area and blue line) and the uncertainty shock (red dashed lines). The results excluding the narrative restriction for demand are similar and available in the Appendix.

**Figure 7:** Responses to Financial and Uncertainty Shocks on Price Markups and Savings Rate

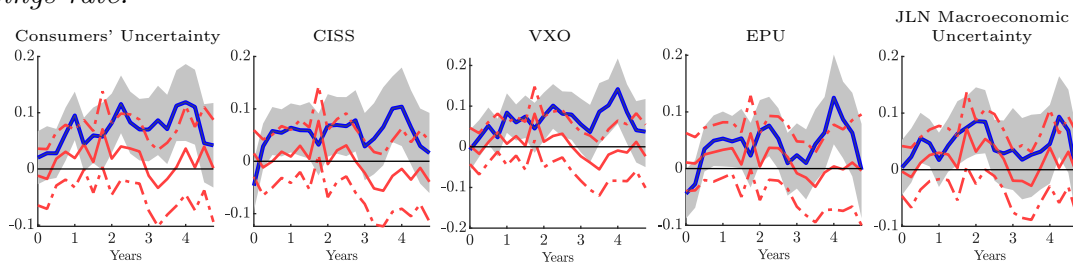
*Markup measure 1:*



*Markup measure 2:*



*Savings rate:*

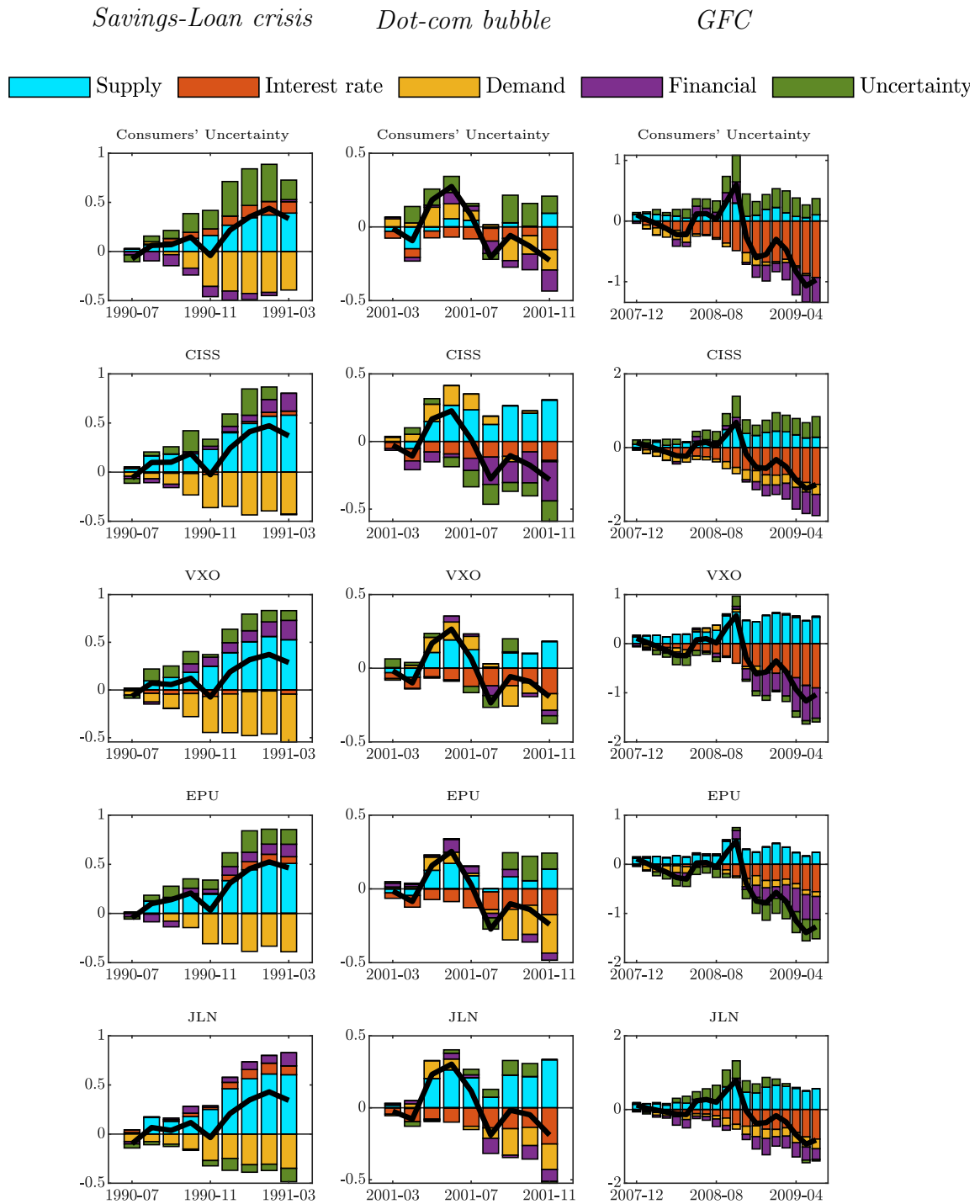


Uncertainty shock  
 Financial shock

*Notes:* The responses of financial and uncertainty shocks on firms' price markups and households' savings rate are obtained using local projections. Median IRFs and 16th and 84th percentiles of the simulated asymptotic distribution (see main text for details).



**Figure 8:** Historical Decomposition of Prices during Recessions for Different Uncertainty Proxies

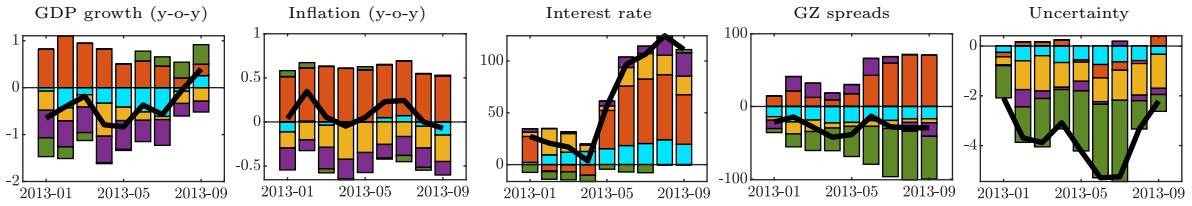


*Notes:* This figure shows the median historical decomposition of goods prices. The represented SVARs contain five variables: GDP, goods prices, 10-year US Treasury, GZ credit spreads and one of the five uncertainty measures. Five shocks are identified using the identification in Table 1 with all narrative restrictions.

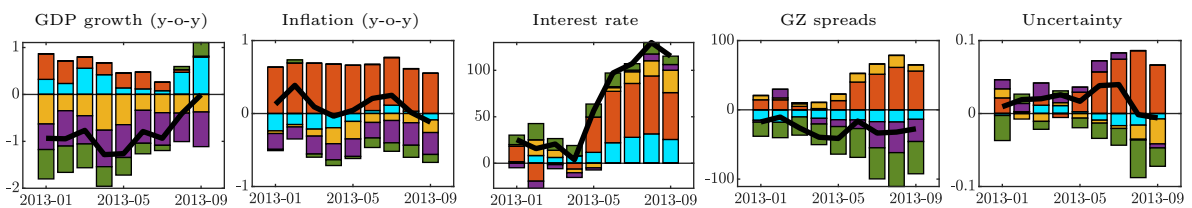
**Figure 9: Historical Shock Decomposition during Taper Tantrum**

Supply Interest rate Demand Financial Uncertainty

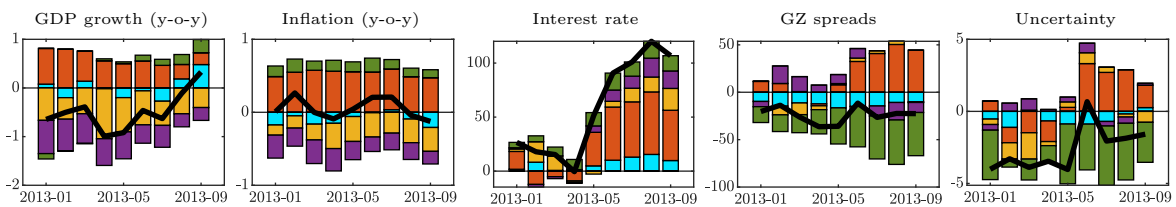
*Consumers' Uncertainty:*



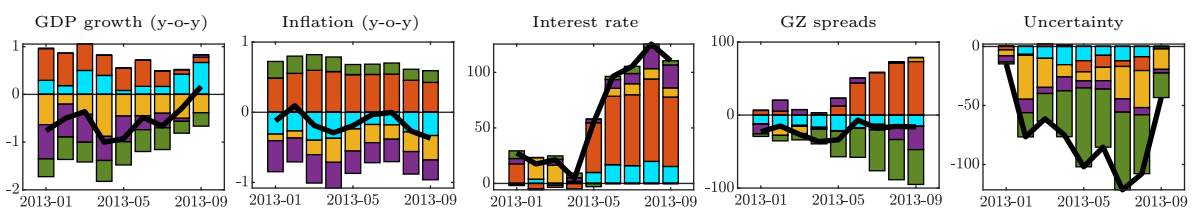
*CISS:*



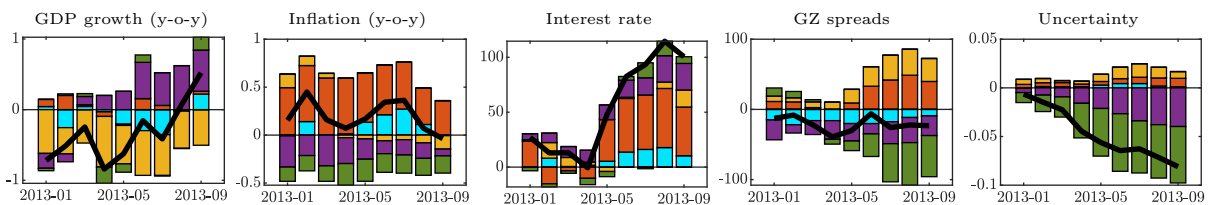
*VXO:*



*EPU:*



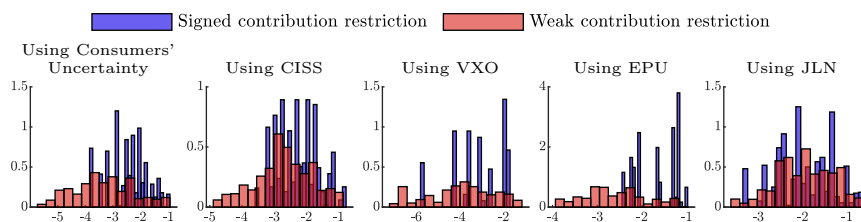
*JLN's Macroeconomic Uncertainty:*



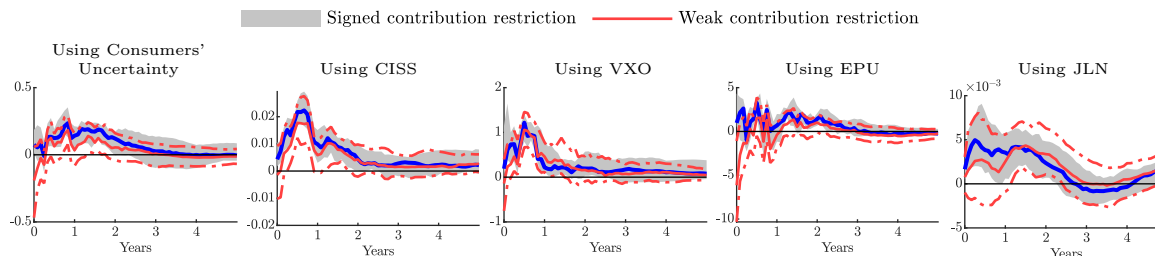
*Notes:* This figure shows the median historical decomposition of the variables in the VAR. The represented SVARs contain five variables: GDP, goods prices, 10-year US Treasury, GZ credit spreads and one of the five uncertainty measures. Five shocks are identified using the identification in Table 1 with all narratives. GDP growth (y-o-y) and inflation (y-o-y) are measured as the year-on-year percent log-difference in real GDP and GDP deflator.

**Figure 10:** Interest Rate Shocks: weak Narrative vs. signed and cross-Narrative

*Panel A: Histograms of Interest Rate Shock in October 1987*

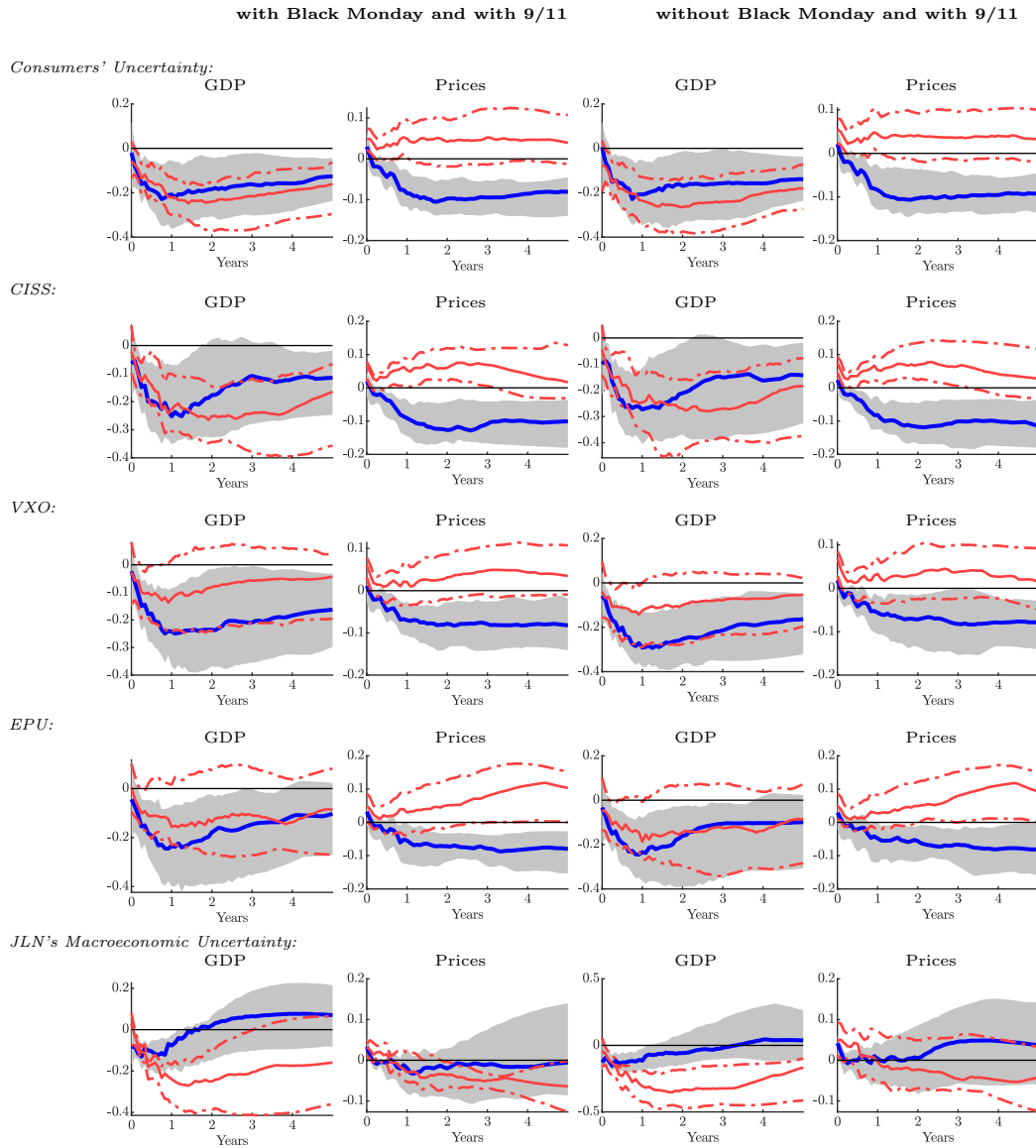


*Panel B: Response of Uncertainty to Interest Rate Shocks*



*Notes:* The represented SVARs contain five variables: GDP, goods prices, 10-year US Treasury rate, GZ credit spreads and an uncertainty variable. Panel A shows the posterior density of the interest rate shocks in October 1987. The thin histograms in blue employ the signed and cross-narrative restrictions (signed contribution restrictions). The wider histograms in red employ the narrative restrictions (weak contribution restrictions) by Antolín-Díaz and Rubio-Ramírez (2018). Panel B shows the respective IRFs associated to one standard deviation interest rate shock. The models are identified using the restrictions listed in Table 1 and the assumption that the interest rate's forecast error in October 1987 is attributed to an expansionary monetary policy shock. In addition, the models identified with signed and cross-narrative restrictions assume that the expansionary monetary policy shock in October 1987 is also the largest contributor among all potential drivers that reduced uncertainty in the same month. All models exclude the demand narrative in order to use more draws.

**Figure 11: Responses to Financial and Uncertainty Shocks using 9/11**



*Notes:* The represented SVARs contain five variables: GDP, goods prices, 10-year US Treasury rate, GZ credit spreads and an uncertainty variable. The identifying assumptions are collected in Table 1. Minnesota prior

Online appendix to:  
Business Cycle Fluctuations:  
Financial Shocks versus Uncertainty Shocks

Roberto A. De Santis\* and Wouter Van der Veken†

September 2022

The appendix is structured as follows. Section I presents the data. Section II describes the construction of the corporate bond spreads. Section III describes the uncertainty measures more in detail. Section IV shows the main drivers of real GDP during recessions. Section V presents a narrative of the main economic forces at play during key economic events. Section VI presents additional results: a) IRFs using only sign restrictions; b) IRFs with narrative sign restrictions, but excluding the narrative on demand shocks; c) the Forecast Error Variance Decomposition (FEVD); d) the historical decomposition of real GDP during recessions; e) IRFs with narrative sign restrictions with the excess bond premium; f) IRFs with narrative sign restrictions when the corporate bond spreads are excluded from the model; g) IRFs with narrative sign restrictions estimated using the Minnesota prior and the sum-of-coefficients prior.

## I Data

We include real GDP, GDP deflator, the 10-year Treasury yield, the GZ corporate bond spreads and, in turn, one of the five uncertainty measures considered in this paper. Real GDP and the GDP deflator enter the model in logs and are interpolated (e.g., Bernanke and Mihov, 1998; Uhlig, 2005). The interpolation of GDP uses industrial production and real retail sales; while the GDP deflator is interpolated using the consumer price index and the producer price index; thereby, including supply and demand considerations. Figure A1 shows the complete dataset.

## II Corporate bond spreads

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 can be captured through 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 non-financial corporations.<sup>1</sup>

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  $k$ ,  $i_t[k]$ ,  $s_{j,t}[k] = R_{j,t}[k] - i_t[k]$  and the corporate bond spread index is a simple average:  $\bar{s}_t[k] = \frac{1}{N_t} \sum_j (s_{j,t}[k])$ , where  $N_t$  is the number of bonds at time  $t$ .<sup>2</sup>

The measure of the tightness of financial market conditions shows the compensation demanded by bond investors for bearing exposure to US non-financial corporate credit risk.<sup>3</sup>

### III Uncertainty measures

#### III.A Consumers' perceived expectations

The uncertainty measure, based on the Michigan consumer sentiment survey, is the fraction of respondents reporting that it is a bad time to purchase a vehicle, because the future is uncertain. A higher index implies higher bad uncertainty about the economic outlook.<sup>4</sup>

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:

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<sup>1</sup>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.

<sup>2</sup>The Treasury yield curve is provided by the FED constructed using the method by Gürkaynak et al. (2007).

<sup>3</sup>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).

<sup>4</sup>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”).

- 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).

### **III.B CISS - Composite Indicator of Systemic Stress**

The US CISS is the US Composite Indicator of Systemic Stress (CISS) constructed by Chavleishvili and Kremer (2021). It is an aggregation of 15 indicators capturing financial stress symptoms, comprising money markets, bond markets, equity markets, and foreign exchange markets.

All indicators are first transformed and thereby homogenized based on their empirical cumulative distribution function (probability integral transform). System-wide stress is then computed by weighing each pair of transformed indicators by its time-varying correlation coefficient (computed as exponentially weighted moving averages) in strict analogy to standard portfolio-theoretic principles.

This methodology allows the CISS to put relatively more weight on situations in which stress prevails in several market segments at the same time, consistent with the idea that only widespread and thus systemic financial stress severely endangers the smooth provision of financial services to the real economy.

The following observables contribute to the measurement of stress:

- money markets: volatility of 3-month Commercial Paper Non-financial (AA-rated) rate, the Ted spread (rate differential between the 3-month LIBOR and the Treasury bill rates), and the rate differential between 3-month commercial paper and the Treasury bill rates;



- bond markets: return volatility of the 10-year Treasury bond, the 10-year yield differential between AAA-rated corporate bonds and Treasury bonds, and the 10-year yield differential between BAA- and AAA-rated corporate bonds;
- equity markets: return volatility, book-price ratios and cumulated maximum percentage index losses over a 2-year moving window (CMAX) separately for non-financial and financial corporations; and
- foreign exchange markets: return volatility of the US Dollar exchange rate vis-à-vis the Euro, the Japanese Yen, and the Canadian Dollar.

### **III.C EPU - Economic Policy Uncertainty**

The EPU is a policy-related economic uncertainty measure, which is constructed by Baker et al. (2016) 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. 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.D Macroeconomic Uncertainty from Jurado et al. (2015)**

Jurado et al. (2015) develop a statistical model with stochastic volatility where macroeconomic uncertainty is recovered as an appropriately weighted average of the forecasting uncertainty of a large number of individual macroeconomic variables. A factor-augmented vector autoregression (FAVAR) is used to construct forecasts for each individual macroeconomic variable. The FAVAR includes the forecasted macroeconomic variables, estimated factors that are obtained from a large set of both macroeconomic and financial variables, squares of these estimated factors, and factors that are obtained from the squared values of the macroeconomic and financial variables. The innovations in the FAVAR are allowed to exhibit time-varying volatility, where the log-volatilities are modelled as independent autoregressive processes. Each variables' forecast uncertainty, is therefore impacted by stochastic

volatility in the factors, in the observed variables, in the squared factors and in the factors of squares. The aggregate macroeconomic uncertainty is obtained as a simple average of the forecast uncertainty across all macroeconomic variables.

### III.E VXO

Since the seminal contribution of Bloom (2009), option-implied stock market volatility may have been the most widely used uncertainty measure in the macroeconomic literature and is known to be strongly linked to other measures of productivity and demand uncertainty.

## IV Output drivers during recessions

According to the National Bureau of Economic Research (NBER), the US economy in our sample was in recession between July 1990 and March 1991 due to the savings-and-loan crisis, between March and November 2001 due to the dot-com bubble, and between December 2007 and June 2009 due to the housing bubble resulting in the Global Financial Crisis (GFC).

**Savings-and-loan crisis.** Our model suggests that uncertainty shocks measured with all five uncertainty measures contributed to the drop in output in this recession. However, the main drivers of the drop in output were supply and demand factors, while financial shocks contributed marginally and with the opposite sign.

**Dot-com bubble.** Uncertainty shocks contributed to the drop in output in this recession, while financial shocks played a marginal role.

**Global Financial Crisis.** During the GFC, both financial shocks and uncertainty shocks contributed to the sharp drop in output with the former having the larger role with all five uncertainty measures. Tightened credit conditions and increased financial stress reinforced each other. The resulting fall in US output was, at that time, the deepest since the Great Depression in the 1930s and the recovery from the GFC was much slower than the recoveries from recessions that were not associated with a financial crisis. After the collapse of Lehman Brothers, the Federal Reserve rapidly lowered the Federal Funds rate to zero. Yet, the 10-year US Treasury rate declined by only 130 basis points between September 2008 and March 2009 and this is interpreted by the model as monetary policy tightening.

## V A shock narrative during main historical episodes

Apart from disentangling the drivers of recessions, through the lenses of our model, we can also look at the economic forces at play during key economic events in our sample. In that respect, we ask our model what the structural shocks are that constituted the collapse of the Long Term Capital Management (LTCM) in 1998, the September 11th terrorist attacks in 2001, the 2011 debt ceiling crisis and the taper tantrum in 2013.

**The 1998 LTCM collapse.** 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. As 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 organized 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 characterized 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, VXO, EPU and macroeconomic uncertainty; while, instead, uncertainty shocks appear to be the most prominent driver when using CISS (see first column of Figure A2).

The crisis was short-lived and our results suggest that the the bailout of LTCM facilitated by the Federal Reserve with a drop in the interest rate shock by two standard deviations in August 1998 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. (2021) 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.

**9/11 2001.** The September 11th terrorist attacks in 2001 on the World Trade Center and the Pentagon not only brought about a human tragedy, but had immediate economic ramifications: disruption of the payments system, a one-week closure of the NYSE, and a temporary suspension of air flights within the United States. After the 9/11 terrorist attacks, consumers' perceived uncertainty, the CISS and EPU increased by about three times as much relative to the previous month, the VXO by half and macroeconomic uncertainty by about 10%. The Federal Open Markets Committee (FOMC) discussed the negative impact of uncertainty after 9/11, lowered interest rates and loaned more than USD 45 billion to financial institutions in order to provide stability to the U.S. economy. By the end of September, Fed lending had returned to pre-September 11 levels and a potential liquidity crunch had been averted. Bloom (2009) used this event as a key uncertainty shock.

Endogenously determined within our model, the uncertainty shocks in September 2001 amounted to four standard deviations (see second column of Figure A2) and the FED engineered an expansionary monetary policy shock in support of financial markets and the entire economy. The results are robust across three out of five uncertainty measures.

**The 2011 debt ceiling crisis.** Rising federal 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,<sup>5</sup> 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.

Our model suggests that both financial shocks and uncertainty shocks were at play in

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<sup>5</sup>The US Constitution grants Congress the power to borrow money and thus mandates that Congress exercises control over federal debt.

August 2011 (see third column of Figure A2) with the use of the VXO (macroeconomic uncertainty) more in favour of an interpretation where the uncertainty (financial) shock is the largest. The 2011 debt ceiling crisis was not only characterized by uncertainty shocks (e.g. Bloom, 2009; Ludvigson et al., 2021), but also by financial shocks due to repricing of risk, which resulted in credit tightening.

**The 2013 taper tantrum.** After the announcement in May 2013 that the Federal Reserve would taper its asset purchase program, the 10-year US Treasury increased by 120 basis points between May and August 2013. The 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 US goods prices were rising, 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 a two standard deviation positive demand shock characterised the US economy in February 2013, which however turned negative 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, a surprisingly hawkish communication by the Federal Reserve in May 2013 driven by at that time available positive macroeconomic data in the first quarter of 2013 triggered the sharp rise in interest rates in the second quarter of 2013.

## VI Additional empirical results

Figure A3 shows the impulse response functions using only sign restrictions at impact (listed in Table 1 in the main text) for the model that includes consumers' uncertainty as the uncertainty measure. It is impossible to assign an economic interpretation to all shocks and the reduced form covariance restrictions alone produce inconclusive results. The figure illustrates the agnosticism we maintain with respect to the macroeconomic responses following financial shocks and uncertainty shocks.

Figures A4-A8 show the complete set of impulse response functions for the five different

benchmark models presented in the paper; that is, the models that include GDP, goods prices, 10-year US Treasury rate, GZ credit spreads, and one of the five uncertainty proxies (consumers' uncertainty in Figure A4, CISS in Figure A5, VXO in Figure A6, EPU in Figure A7 or JLN macroeconomic uncertainty in Figure A8). These results are shown using the baseline identification scheme described in Table 1 in the main text and the identification scheme that excludes the narrative restriction on the demand shock.

Figure A9 shows the FEVD for each of the variables in our model providing the results for the model with consumers' perceived uncertainty and the CISS.

Figure A10 shows the historical decomposition of GDP during recessions for different uncertainty proxies.

Figure A11 shows the response of price mark-ups to financial and uncertainty shocks using the identification scheme that excludes the narrative restriction on the demand shock.

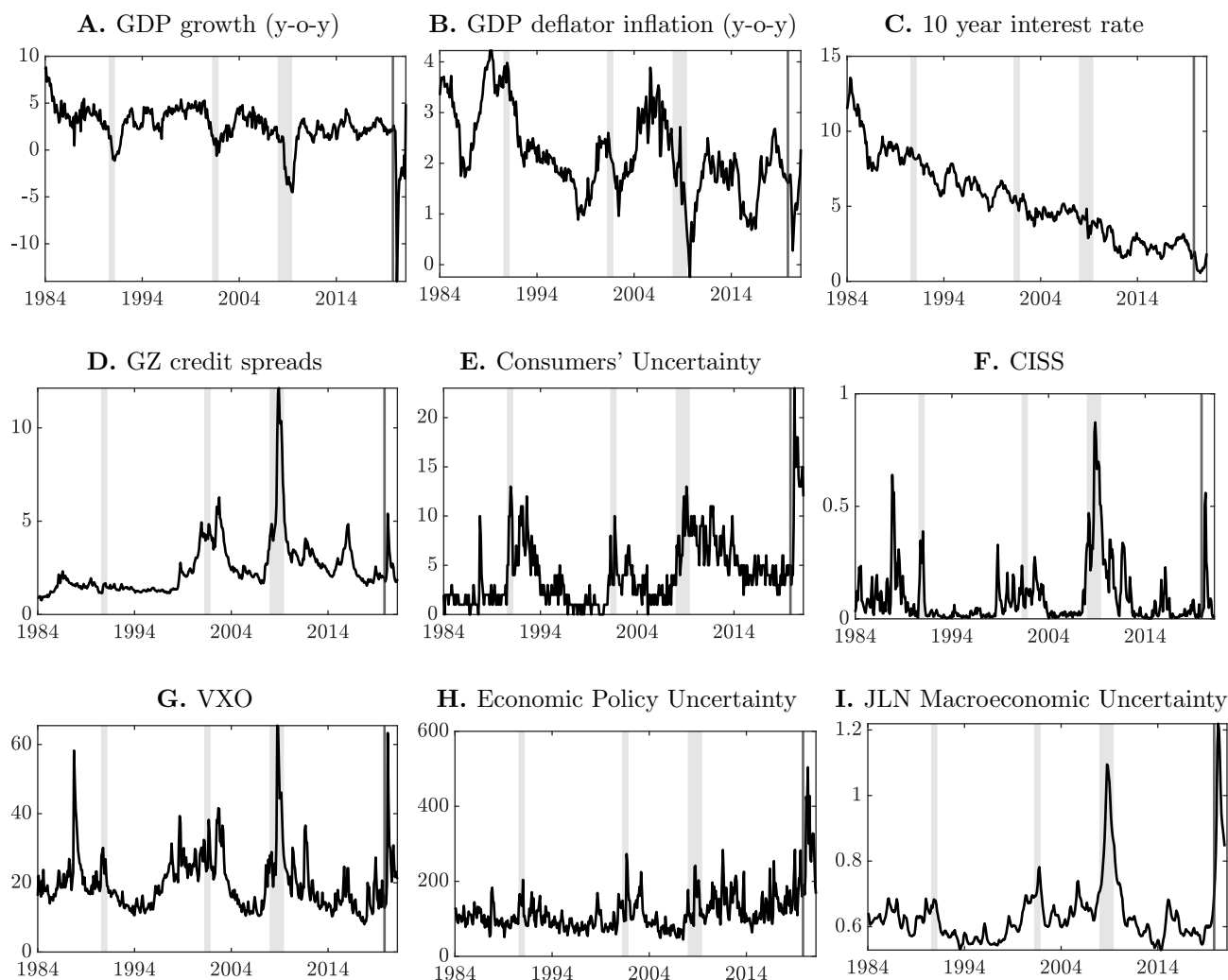
Figures A12-A16 show the robustness of the impulse response functions with respect to using the Excess Bond Premium (EBP) obtained from Gilchrist et al. (2009), instead of the GZ credit spreads.

Figure A17 shows the robustness of the responses to (i) uncertainty shocks, if we exclude the GZ credit spreads from the model and financial shocks are not identified; (i) financial shocks, if we exclude the uncertainty gauge from the model and uncertainty shocks are not identified.

Figure A18 shows the IRFs estimated using the Minnesota prior and the sum-of-coefficients prior.

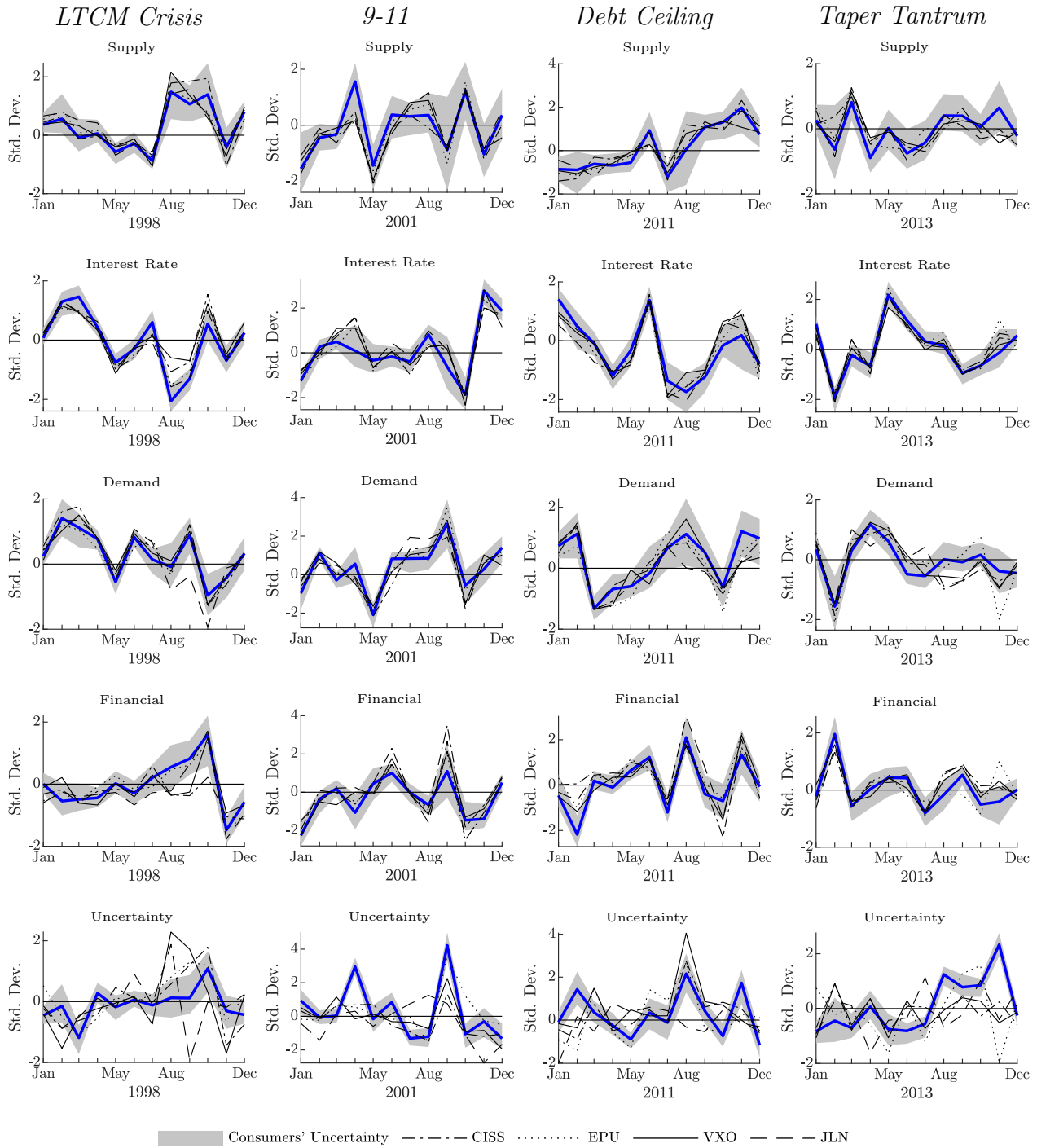
## VII Figures

**Figure A1:** The Database with Alternative Uncertainty Measures



*Notes:* GDP growth (y-o-y) and GDP deflator inflation (y-o-y) are measured as the year-on-year percent log-difference in real GDP and GDP deflator. Real GDP and GDP deflator in log-levels enter in the VAR. The GZ corporate credit spread is constructed using the approach suggested by Gilchrist et al. (2009) and Gilchrist and Zakrajšek (2012). 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 JLN macroeconomic uncertainty is the measure suggested by Jurado et al. (2015).

**Figure A2: Structural Shocks in Selected Periods**

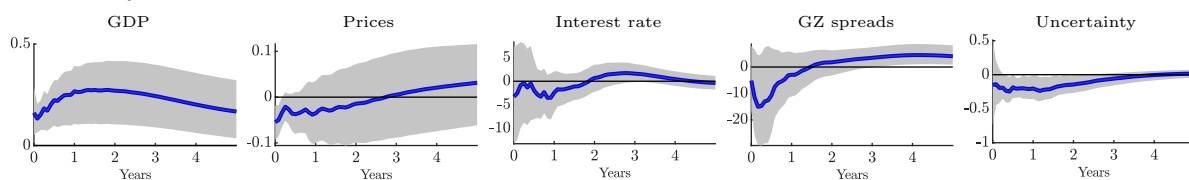


*Notes:* The represented SVARs contain five variables: GDP, goods prices, 10-year US Treasury, GZ credit spreads and a measure of uncertainty. Five shocks are identified using the identification in Table 1 with all narrative restrictions. The blue line and shaded area represent the median, 16th and 84th percentiles of the shocks identified using the SVAR that includes consumers' uncertainty; while the medians of the models using the VXO, JLN macroeconomic uncertainty, CISS and EPU are depicted, respectively, by the thin black line, the dashed line, the dash-dotted line, and the dotted line.

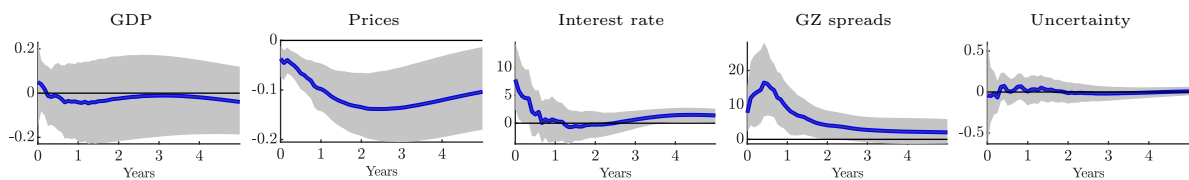


**Figure A3:** Unidentified IRFs following from Impact Sign Restrictions Only

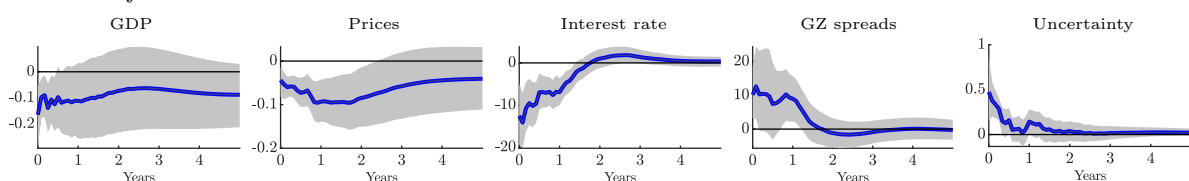
*Unidentified shock 1:*



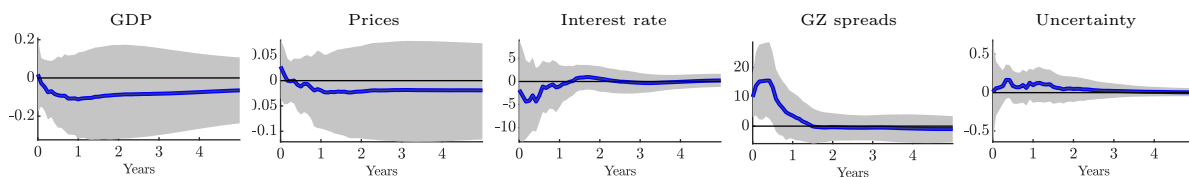
*Unidentified shock 2:*



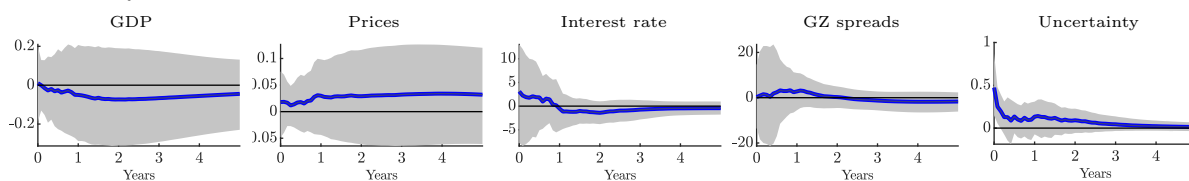
*Unidentified shock 3:*



*Unidentified shock 4:*



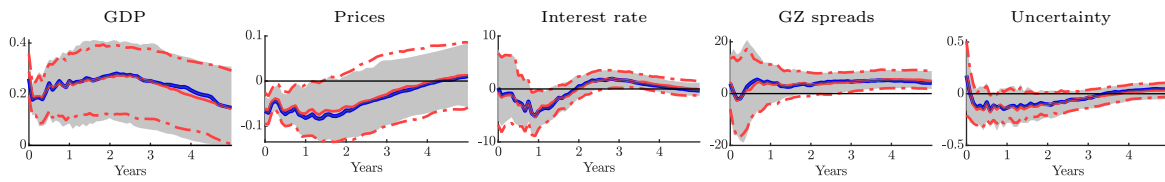
*Unidentified shock 5:*



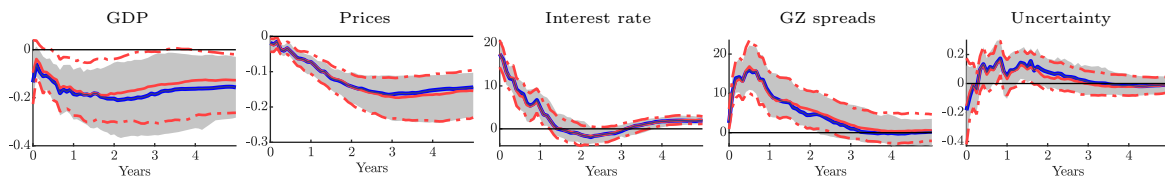
*Notes:* The VAR contains five variables: GDP, goods prices, 10-year US Treasury yield, GZ credit spreads and consumers' uncertainty. The VAR uses only the sign restrictions described in Table 1. The median IRFs are shown in blue and the corresponding posterior 68% credible sets are represented by the shaded area.

**Figure A4:** Benchmark SVAR with Consumers' Uncertainty: IRFs and effect of including NSR for Demand shock

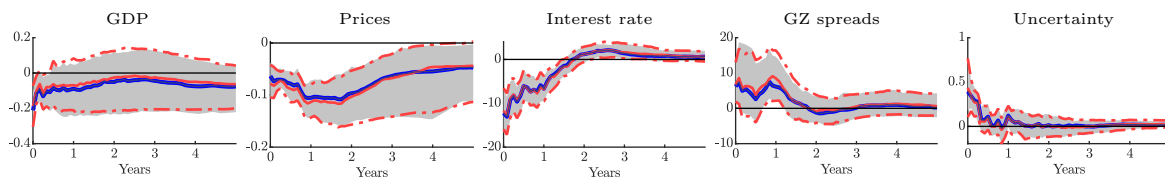
*Supply / cost-push shocks:*



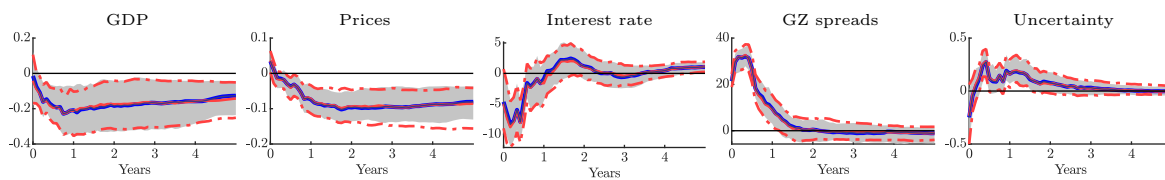
*Interest rate shocks:*



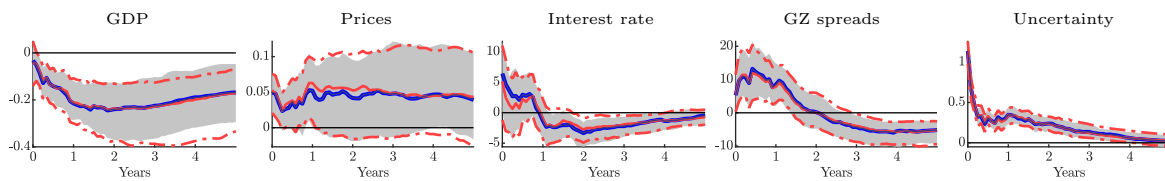
*Demand shocks:*



*Financial shocks:*



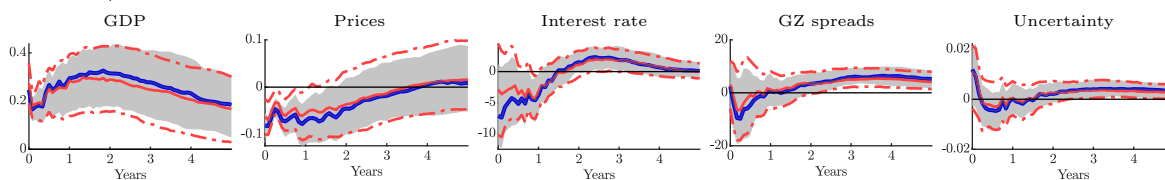
*Uncertainty shocks:*



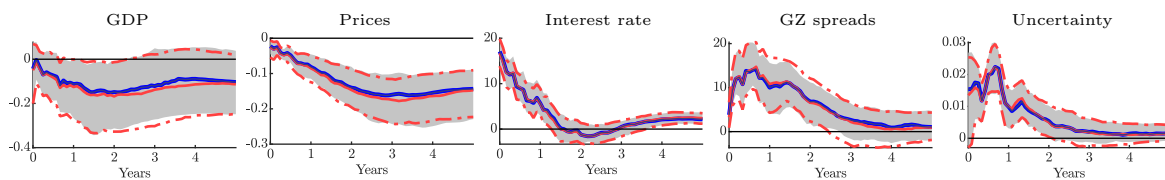
*Notes:* The represented SVARs contain five variables: GDP, goods prices, 10-year US Treasury rate, GZ credit spreads and consumers' uncertainty. Each panel shows the median IRFs and the corresponding posterior 68% credible sets for the results that are obtained using the full set of identifying restrictions (see Table 1 in the main text; blue line and shaded area) and for the results that are obtained by excluding the narrative restriction for the demand shock (full and dashed red lines).

**Figure A5:** Benchmark SVAR with CISS: IRFs and effect of including NSR for Demand shock

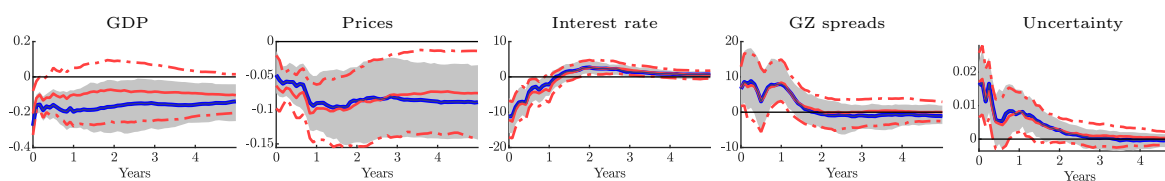
*Supply / cost-push shocks:*



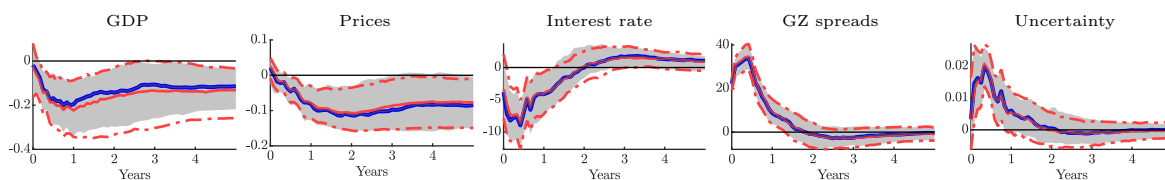
*Interest rate shocks:*



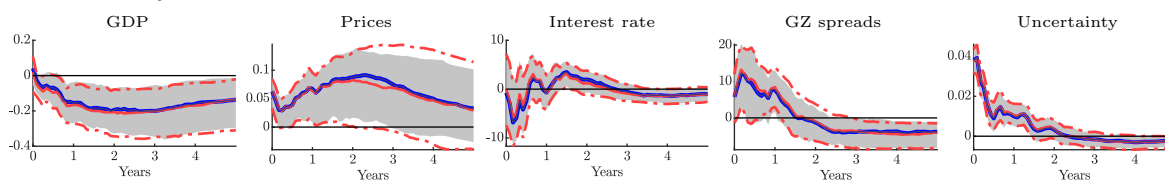
*Demand shocks:*



*Financial shocks:*



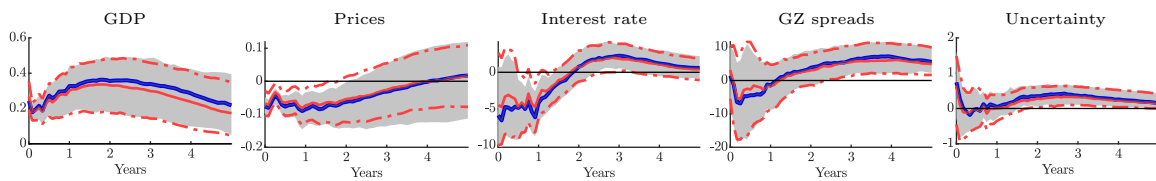
*Uncertainty shocks:*



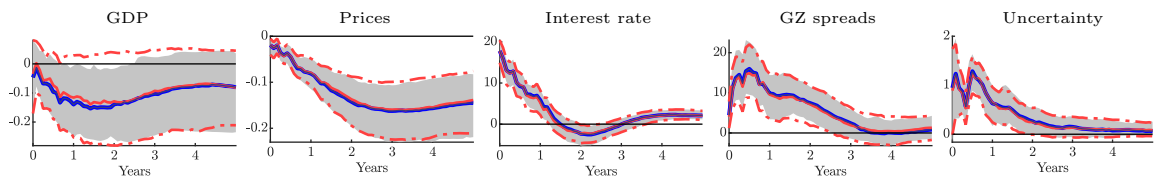
*Notes:* The represented SVARs contain five variables: GDP, goods prices, 10-year US Treasury rate, GZ credit spreads and CISS. Each panel shows the median IRFs and the corresponding posterior 68% credible sets for the results that are obtained using the full set of identifying restrictions (see Table 1 in the main text; blue line and shaded area) and for the results that are obtained by excluding the narrative restriction for the demand shock (full and dashed red lines).

**Figure A6:** Benchmark SVAR with VXO: IRFs and effect of including NSR for Demand shock

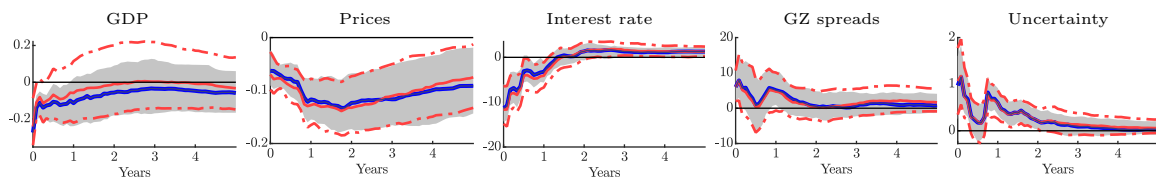
*Supply / cost-push shocks:*



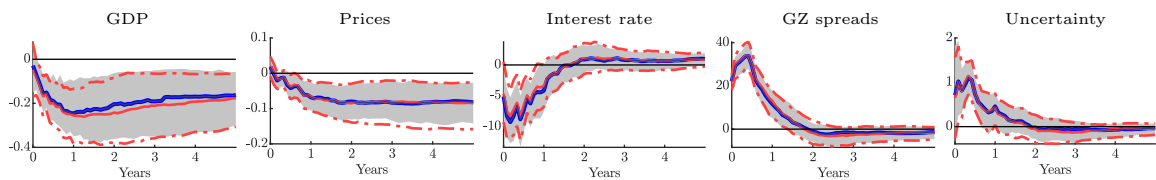
*Interest rate shocks:*



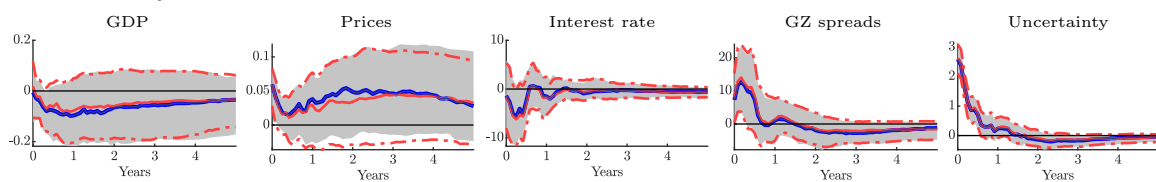
*Demand shocks:*



*Financial shocks:*



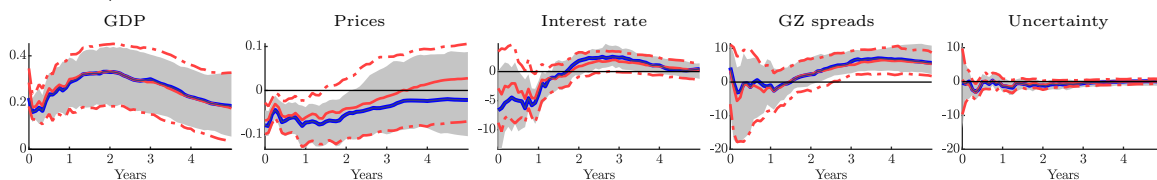
*Uncertainty shocks:*



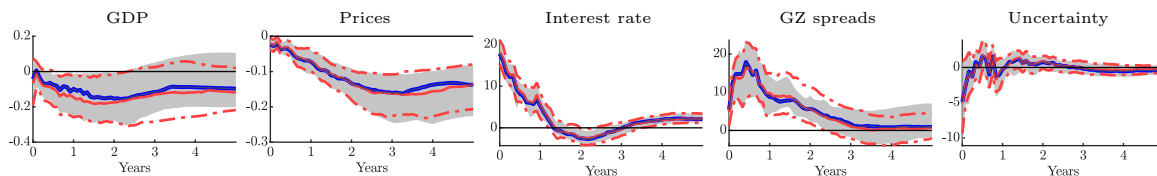
*Notes:* The represented SVARs contain five variables: GDP, goods prices, 10-year US Treasury rate, GZ credit spreads and VXO. Each panel shows the median IRFs and the corresponding posterior 68% credible sets for the results that are obtained using the full set of identifying restrictions (see Table 1 in the main text; blue line and shaded area) and for the results that are obtained by excluding the narrative restriction for the demand shock (full and dashed red lines).

**Figure A7:** Benchmark SVAR with EPU: IRFs and effect of including NSR for Demand shock

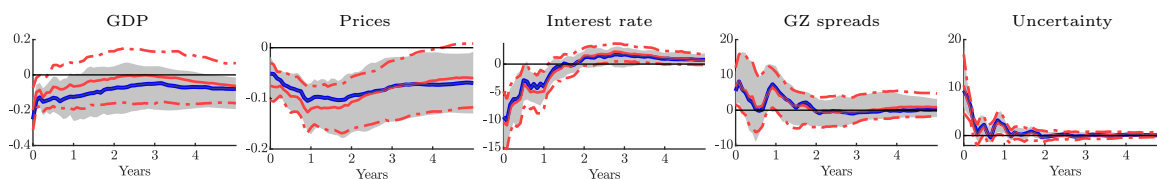
*Supply / cost-push shocks:*



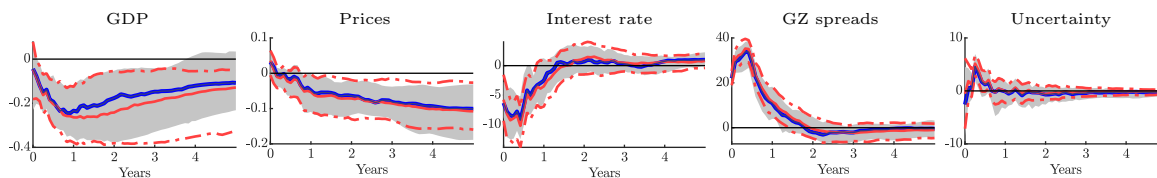
*Interest rate shocks:*



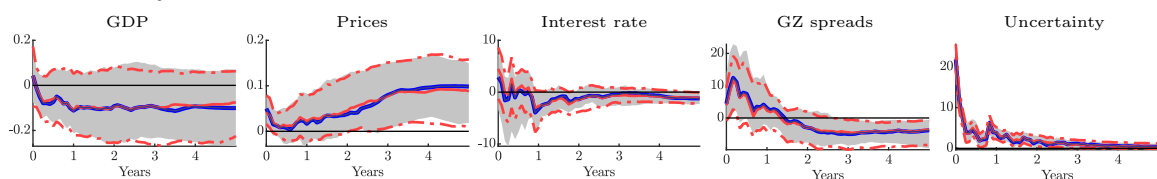
*Demand shocks:*



*Financial shocks:*



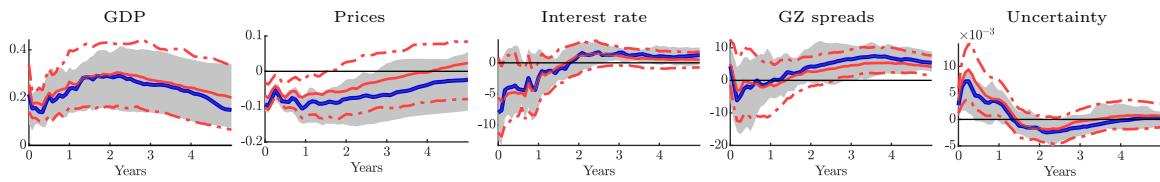
*Uncertainty shocks:*



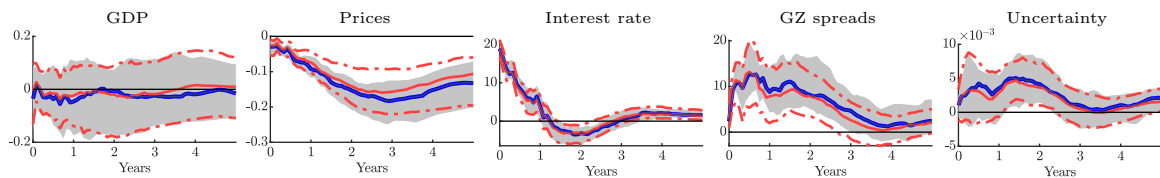
*Notes:* The represented SVARs contain five variables: GDP, goods prices, 10-year US Treasury rate, GZ credit spreads and EPU. Each panel shows the median IRFs and the corresponding posterior 68% credible sets for the results that are obtained using the full set of identifying restrictions (see Table 1 in the main text; blue line and shaded area) and for the results that are obtained by excluding the narrative restriction for the demand shock (full and dashed red lines).

**Figure A8:** Benchmark SVAR with JLN Macroeconomic Uncertainty: IRFs and effect of including NSR for Demand shock

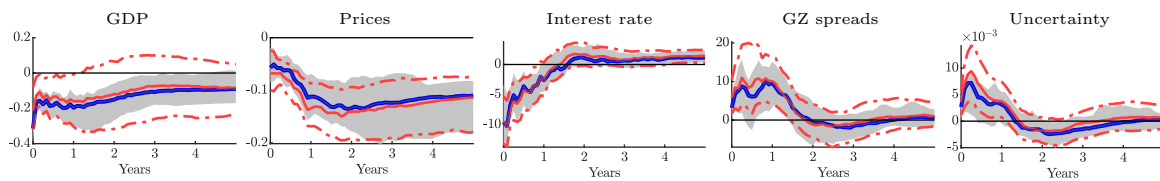
*Supply / cost-push shocks:*



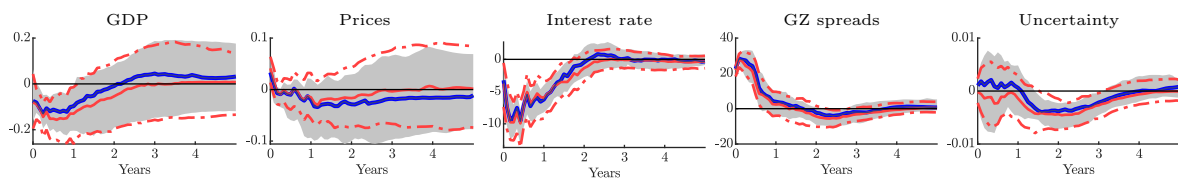
*Interest rate shocks:*



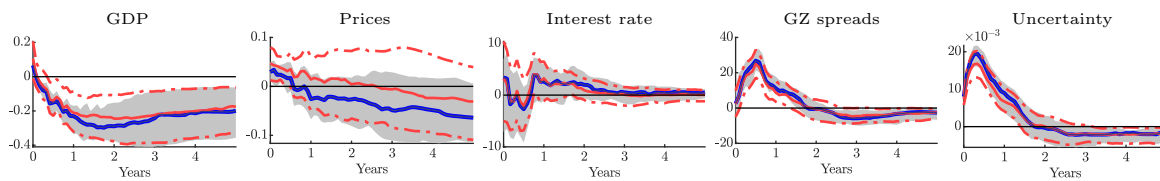
*Demand shocks:*



*Financial shocks:*



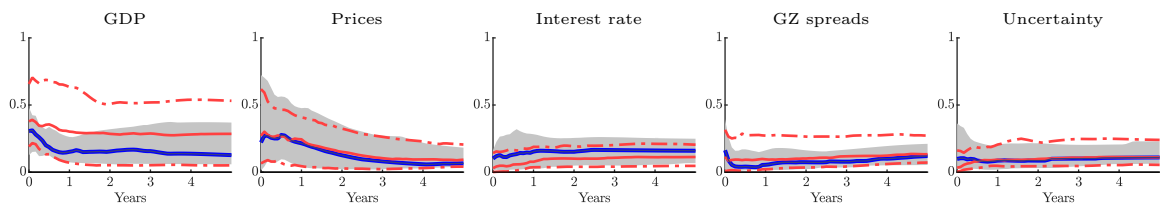
*Uncertainty shocks:*



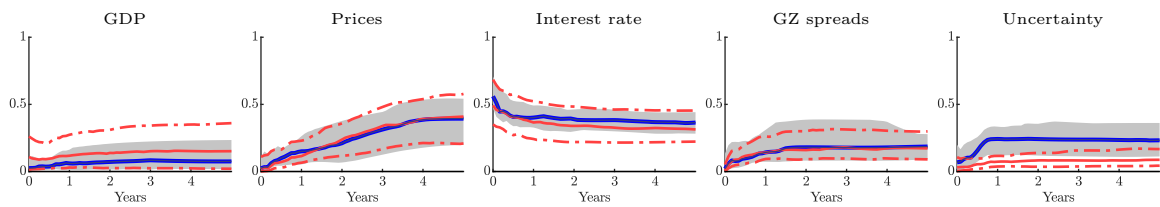
*Notes:* The represented SVARs contain five variables: GDP, goods prices, 10-year US Treasury rate, GZ credit spreads and JLN macroeconomic uncertainty. Each panel shows the median IRFs and the corresponding posterior 68% credible sets for the results that are obtained using the full set of identifying restrictions (see Table 1 in the main text; blue line and shaded area) and for the results that are obtained by excluding the narrative restriction for the demand shock (full and dashed red lines).

**Figure A9:** Forecast-error variance decomposition using Consumers' Uncertainty and CISS

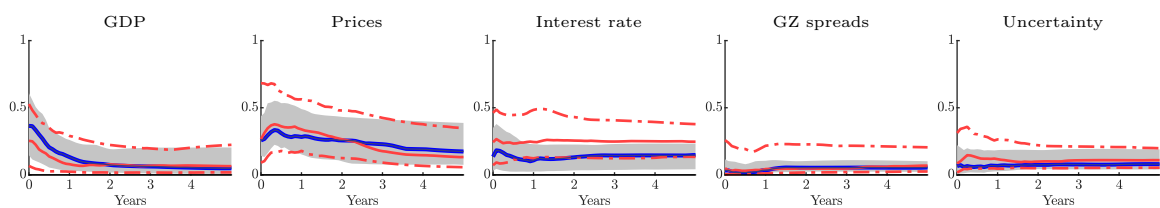
*Supply / cost-push shocks:*



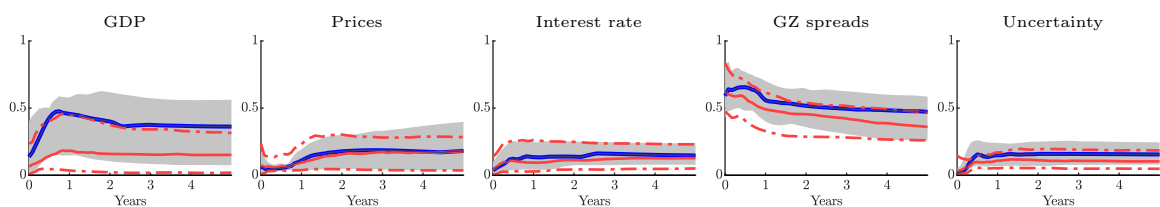
*Interest rate shocks:*



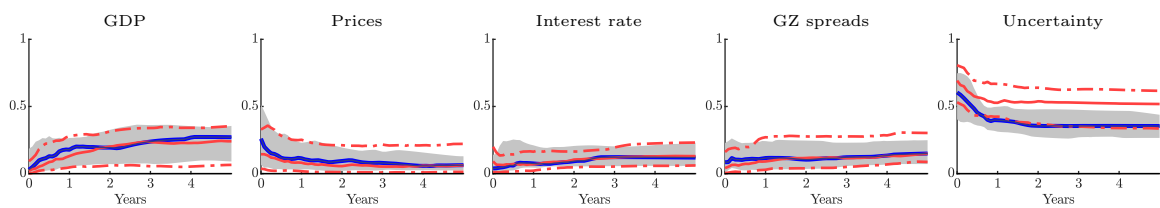
*Demand shocks:*



*Financial shocks:*



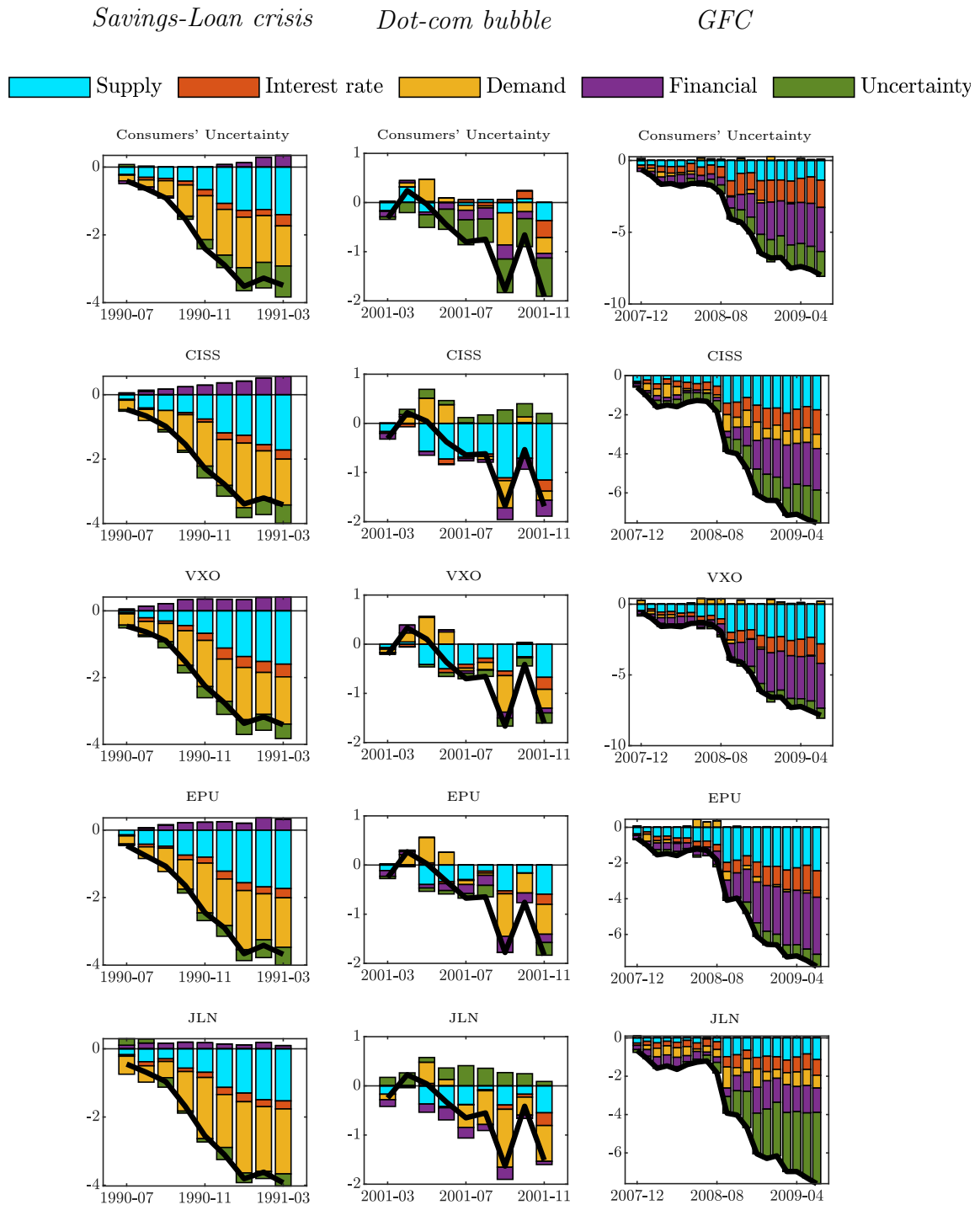
*Uncertainty shocks:*



Consumers' uncertainty (left)  
 CISS (right)

*Notes:* The represented SVARs contain five variables: GDP, goods prices, 10-year US Treasury rate, GZ credit spreads and either consumers' uncertainty or CISS. The identifying assumptions are collected in Table 1. Each panel shows the median IRFs and the corresponding posterior 68% credible sets (dashed red lines and shaded areas). The results excluding the narrative restriction for demand are similar and available in the Appendix.

**Figure A10:** Historical Decomposition of GDP during Recessions for Different Uncertainty Proxies

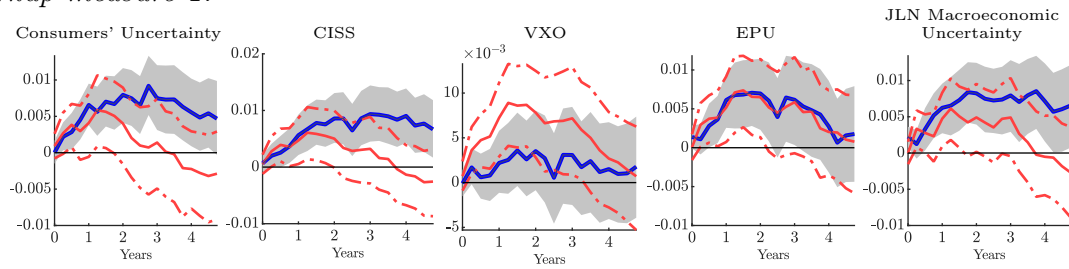


*Notes:* This figure shows the historical decomposition of shocks on goods prices. The represented SVARs contain five variables: GDP, goods prices, 10-year US Treasury, GZ credit spreads and one of the five uncertainty measures. Five shocks are identified using the identification in Table 1 with all narrative restrictions.

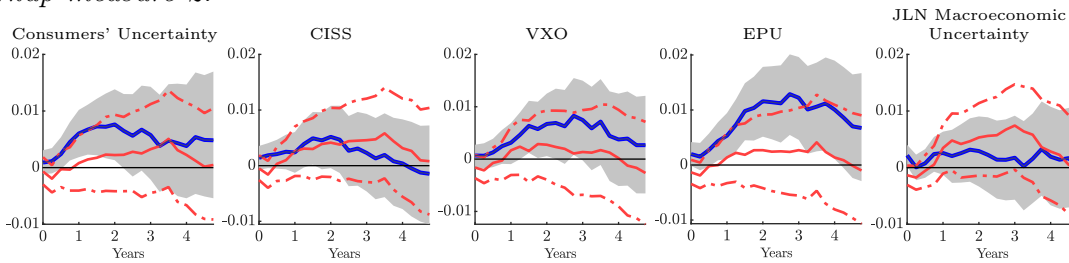


**Figure A11:** Responses to Financial and Uncertainty Shocks on Price Markups and Savings Rate excl. Demand Narrative

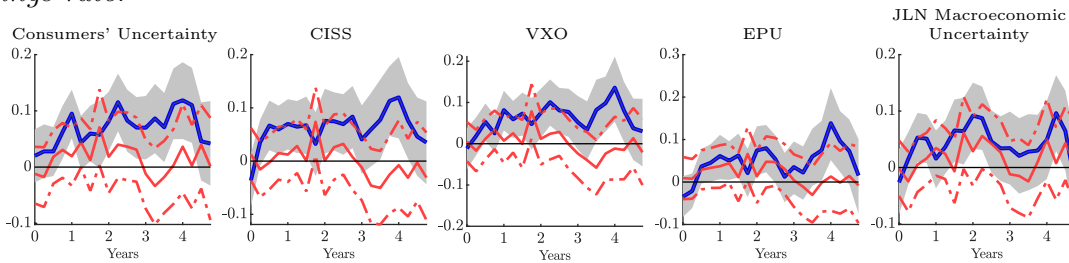
*Markup measure 1:*



*Markup measure 2:*



*Savings rate:*

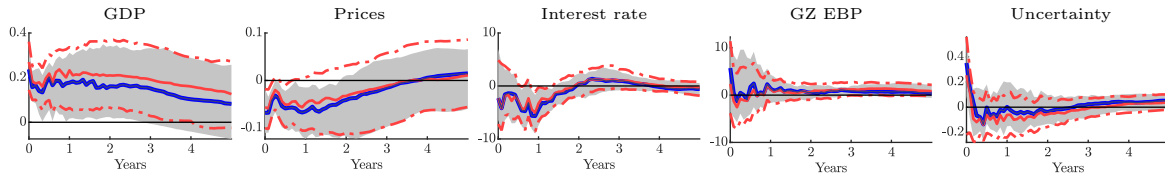


Uncertainty shock  
 Financial shock

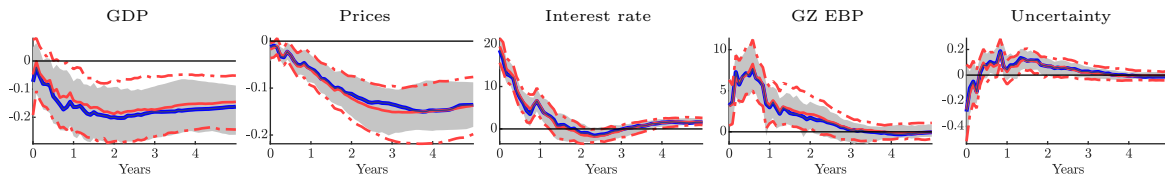
*Notes:* The responses of financial and uncertainty shocks on firms' price markups and households' savings rate are obtained using local projections. The financial and uncertainty shocks are identified using the restrictions from Table 1, excluding the narrative sign restriction for the demand shock. Median IRFs and 16th and 84th percentiles of the simulated asymptotic distribution (see main text for details).

**Figure A12:** SVAR with EBP and Consumers' Uncertainty: IRFs and effect of including NSR for Demand shock

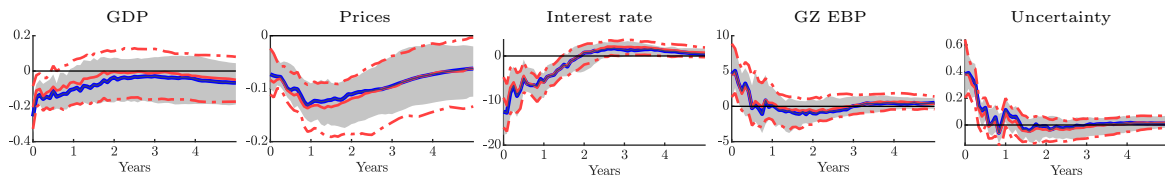
*Supply / cost-push shocks:*



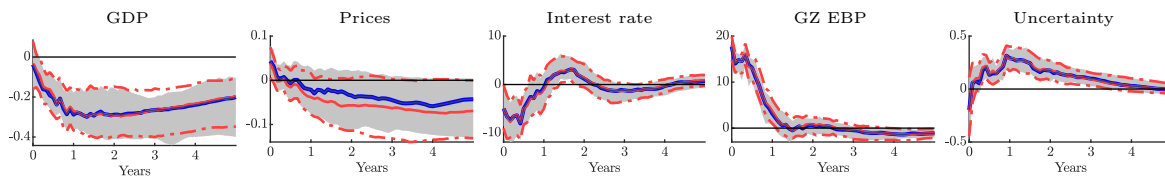
*Interest rate shocks:*



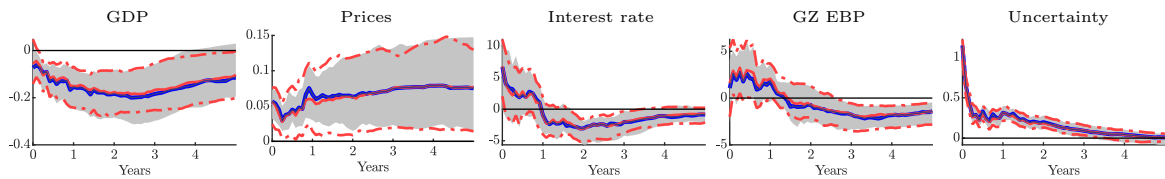
*Demand shocks:*



*Financial shocks:*



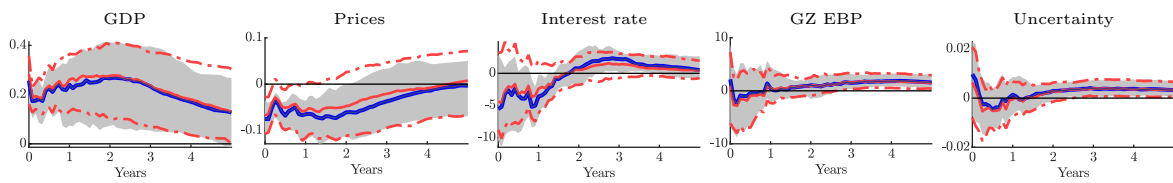
*Uncertainty shocks:*



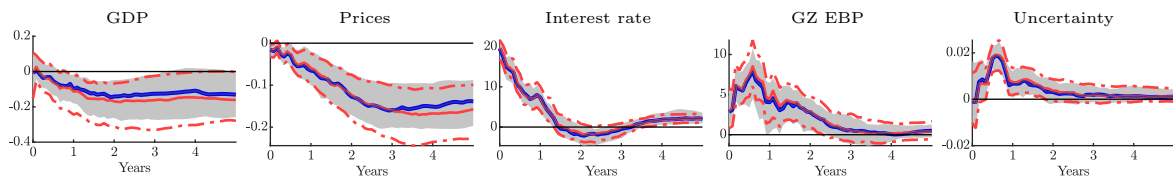
*Notes:* The represented SVARs contain five variables: GDP, goods prices, 10-year US Treasury rate, GZ excess bond premium (EBP) and consumers' uncertainty. Each panel shows the median IRFs and the corresponding posterior 68% credible sets for the results that are obtained using the full set of identifying restrictions (see Table 1 in the main text; blue line and shaded area) and for the results that are obtained by excluding the narrative restriction for the demand shock (full and dashed red lines).

**Figure A13:** SVAR with EBP and CISS: IRFs and effect of including NSR for Demand shock

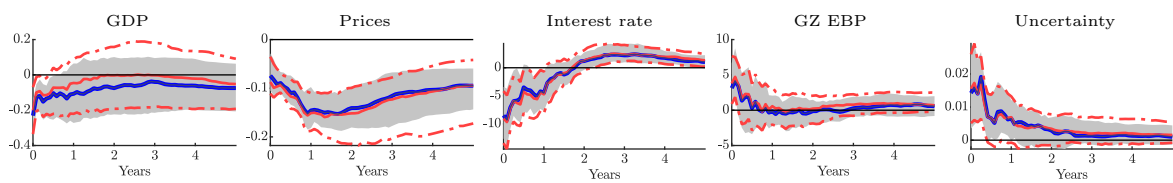
*Supply / cost-push shocks:*



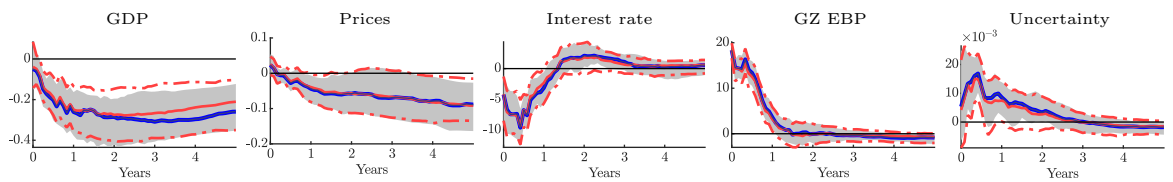
*Interest rate shocks:*



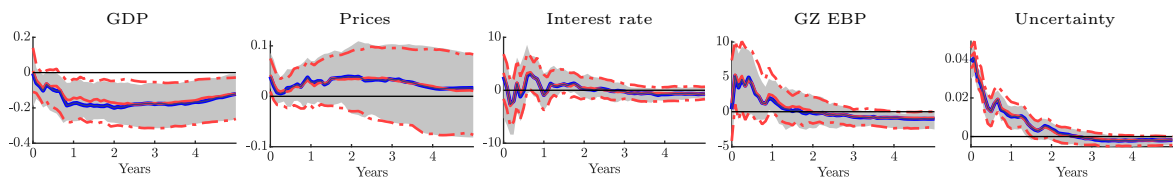
*Demand shocks:*



*Financial shocks:*



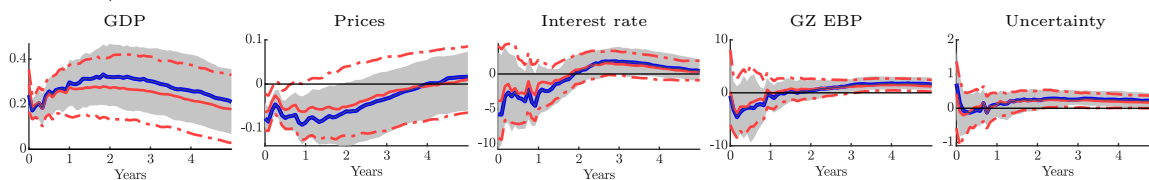
*Uncertainty shocks:*



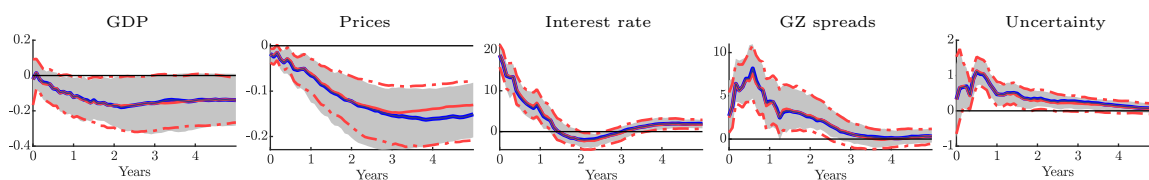
*Notes:* The represented SVARs contain five variables: GDP, goods prices, 10-year US Treasury rate, GZ excess bond premium (EBP) and CISS. Each panel shows the median IRFs and the corresponding posterior 68% credible sets for the results that are obtained using the full set of identifying restrictions (see Table 1 in the main text; blue line and shaded area) and for the results that are obtained by excluding the narrative restriction for the demand shock (full and dashed red lines).

**Figure A14: SVAR with EBP and VXO: IRFs and effect of including NSR for Demand shock**

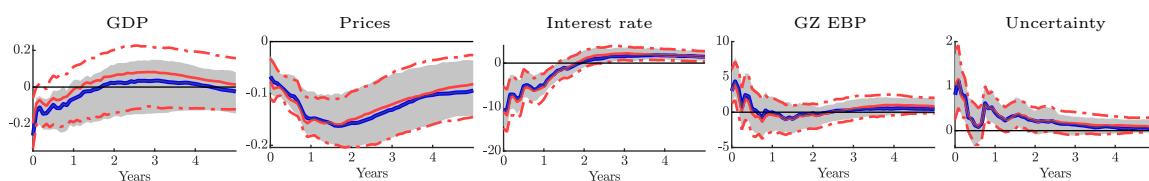
*Supply / cost-push shocks:*



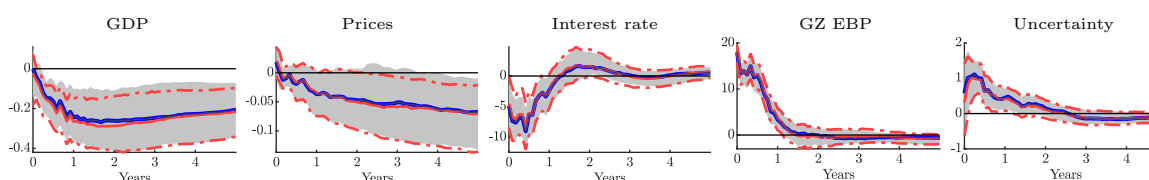
*Interest rate shocks:*



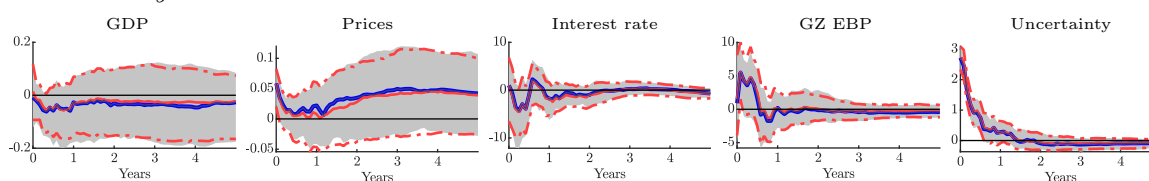
*Demand shocks:*



*Financial shocks:*



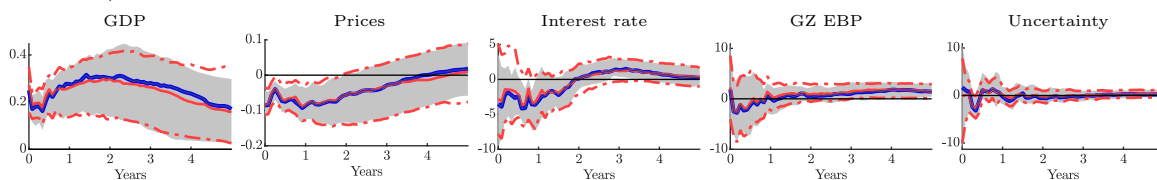
*Uncertainty shocks:*



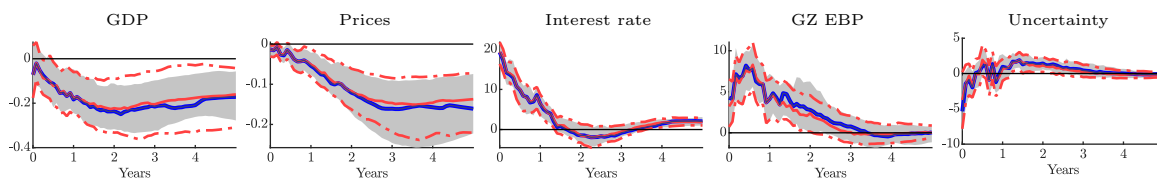
*Notes:* The represented SVARs contain five variables: GDP, goods prices, 10-year US Treasury rate, GZ excess bond premium (EBP) and VXO. Each panel shows the median IRFs and the corresponding posterior 68% credible sets for the results that are obtained using the full set of identifying restrictions (see Table 1 in the main text; blue line and shaded area) and for the results that are obtained by excluding the narrative restriction for the demand shock (full and dashed red lines).

**Figure A15: SVAR with EBP and EPU: IRFs and effect of including NSR for Demand shock**

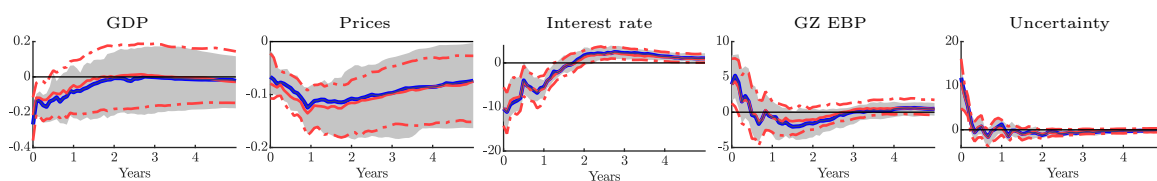
*Supply / cost-push shocks:*



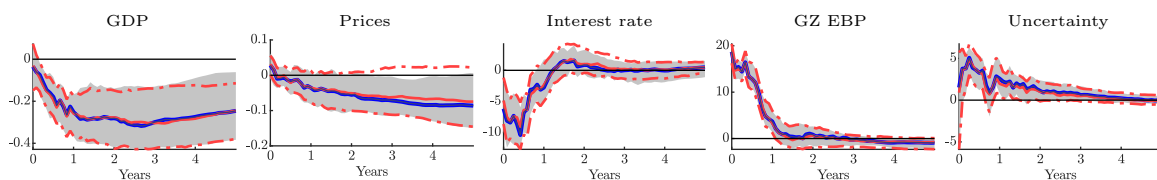
*Interest rate shocks:*



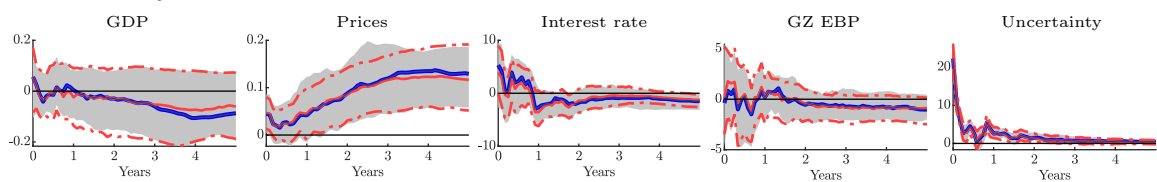
*Demand shocks:*



*Financial shocks:*



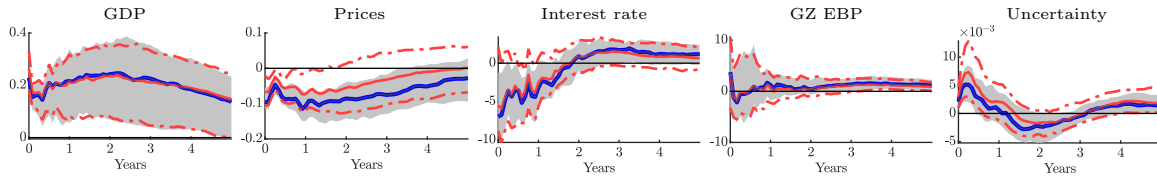
*Uncertainty shocks:*



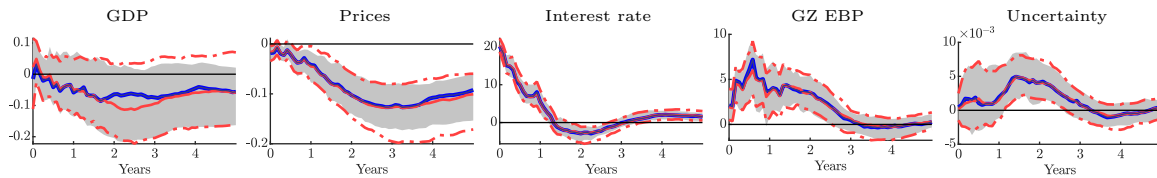
*Notes:* The represented SVARs contain five variables: GDP, goods prices, 10-year US Treasury rate, GZ excess bond premium (EBP) and EPU. Each panel shows the median IRFs and the corresponding posterior 68% credible sets for the results that are obtained using the full set of identifying restrictions (see Table 1 in the main text; blue line and shaded area) and for the results that are obtained by excluding the narrative restriction for the demand shock (full and dashed red lines).

**Figure A16:** SVAR with EBP and JLN Macroeconomic Uncertainty: IRFs and effect of including NSR for Demand shock

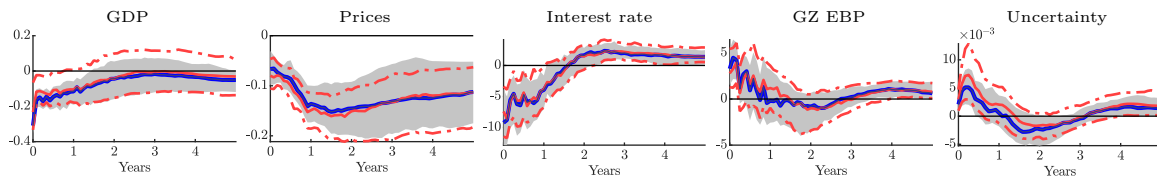
*Supply / cost-push shocks:*



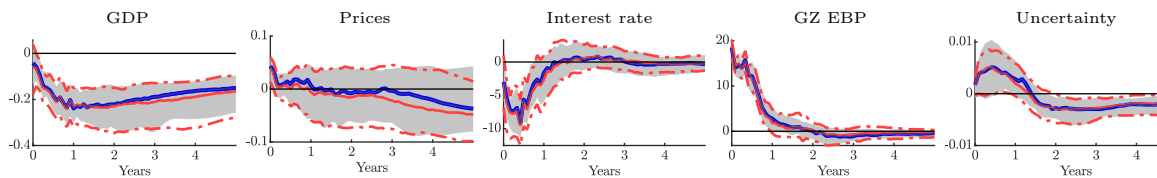
*Interest rate shocks:*



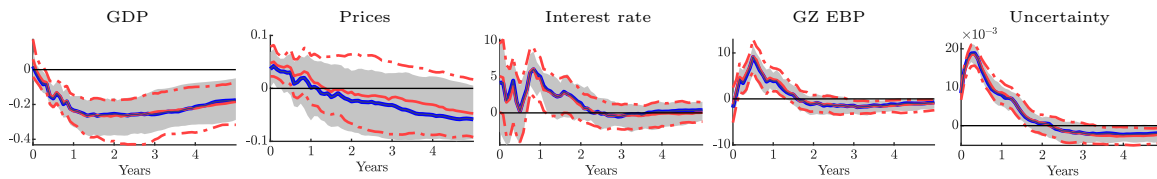
*Demand shocks:*



*Financial shocks:*



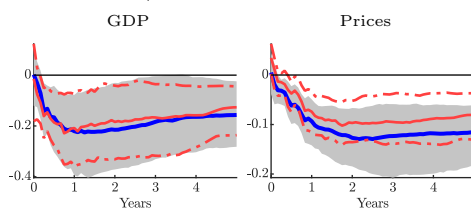
*Uncertainty shocks:*



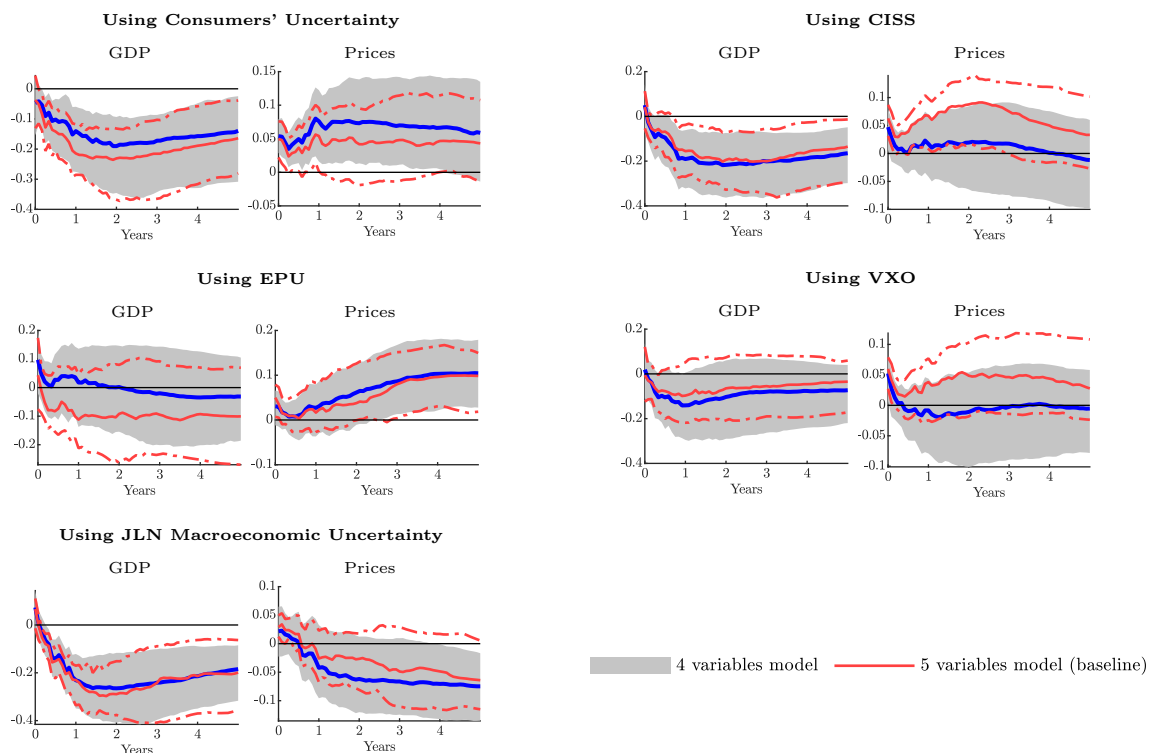
*Notes:* The represented SVARs contain five variables: GDP, goods prices, 10-year US Treasury rate, GZ credit spreads and JLN macroeconomic uncertainty. Each panel shows the median IRFs and the corresponding posterior 68% credible sets for the results that are obtained using the full set of identifying restrictions (see Table 1 in the main text; blue line and shaded area) and for the results that are obtained by excluding the narrative restriction for the demand shock (full and dashed red lines).

**Figure A17:** 4-Variable SVARs excluding either the uncertainty shock or the financial shock

*Financial shock (excludes uncertainty measures)*

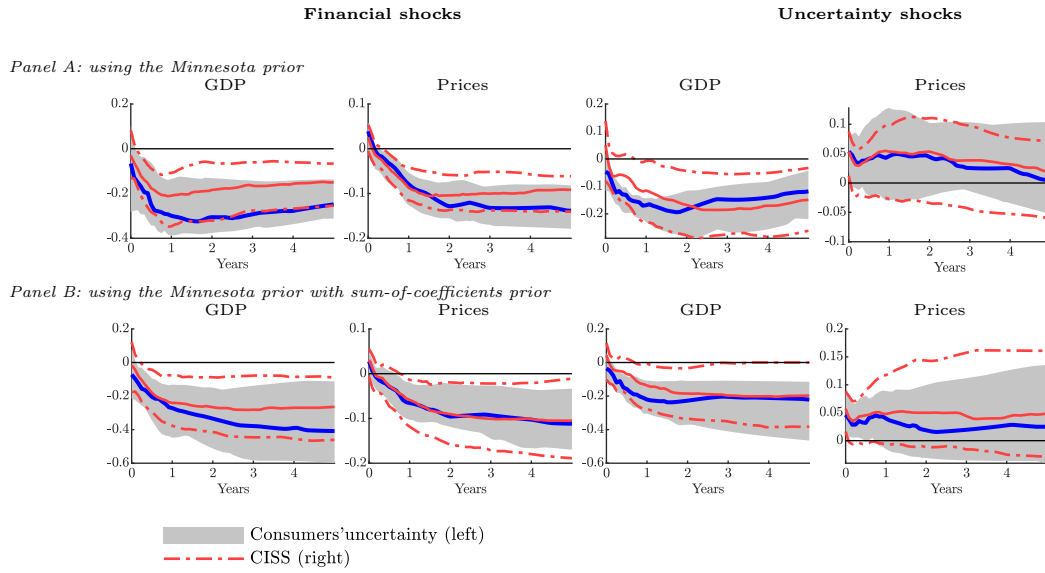


*Uncertainty shocks (excludes GZ spreads)*



*Notes:* The represented SVARs contain four variables: GDP, goods prices, 10-year US Treasury rate and an uncertainty variable (rows 2 to 4) or GZ credit spreads (row 1). The identifying assumptions are collected in Table 1 but exclude the restrictions for the financial (uncertainty) shocks, when identifying the uncertainty (financial) shocks. Each panel shows each models' median IRF in blue and the corresponding posterior 68% credible sets as the shaded area. The median IRFs in red and the corresponding credible sets are, for comparison, taken from the baseline models in Figures 5 and 6. For the 4-variable model that excludes the uncertainty shock (last row), the baseline 5-variable IRFs are taken from the model that includes consumers' uncertainty.

**Figure A18:** Responses to Financial and Uncertainty Shocks using alternative Bayesian Methods



*Notes:* The represented SVARs contain five variables: GDP, goods prices, 10-year US Treasury rate, GZ credit spreads and an uncertainty variable. The identifying assumptions are collected in Table 1. Panel A employs the Minnesota prior and Panel B employs the Minnesota prior with the sum-of-coefficients prior.



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