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To sign or not to sign? On the response of prices to financial and uncertainty shocks

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Non-technical summary

Research Question

This paper empirically analyzes the role of uncertainty and financial shocks for consumer prices in the United States and the euro area. Although the macroeconomic effects of uncertainty and financial shocks have attracted significant attention in quantitative macroeconomics, the empirical evidence on the impact of these shocks on prices is still scarce. Moreover, while theoretical contributions based on microfounded DSGE models generally deliver unambiguous output effects in response to these shocks, the implied price reactions turn out to vary across the suggested modeling setups from a qualitative perspective.

Contribution

In this paper, we propose a sign-identified structural vector autoregressive (SVAR) model framework that allows us to disentangle uncertainty and financial shocks, while being agnostic about the effects that these disturbances have on prices. Thus, we are not only able to provide empirical evidence on the theoretical debate about the price effects of uncertainty and financial shocks, but also to account for recent findings stressing the importance of jointly modeling these disturbances. We apply the SVAR model to US euro-area data.

Results

Our main findings can be summarized as follows. First, we find that uncertainty and financial shocks play a prominent role for output fluctuations in both economies. Second, we confirm the theoretical ambiguity of price reactions to both types of disturbances. Third, constraining prices to co-move with output, as done in a number of recent empirical applications, can imply underestimating the role of financial and uncertainty shocks for real activity.

Nichttechnische Zusammenfassung

Fragestellung

Das vorliegende Papier analysiert den Einfluss von Unsicherheits- und Finanzmarktschocks auf die Verbraucherpreise in den USA und dem Euroraum. Obwohl die makroökonomischen Effekte von Unsicherheits- und Finanzmarktschocks in den vergangenen Jahren intensiver untersucht worden sind, ist die empirische Evidenz zu den Preiseffekten dieser beiden Störgrößen gering. Darüber hinaus liefern theoretische Beiträge unter Verwendung mikrofundierter DSGE Modelle zwar zumeist eindeutige Effekte dieser Schocks auf das Bruttoinlandsprodukt. Es zeigt sich jedoch, dass ihr Einfluss auf Preise in Abhängigkeit von der gewählten Modellspezifikation in qualitativer Hinsicht variieren kann.

Beitrag

Dieses Papier nutzt ein mittels Vorzeichenrestriktionen identifiziertes strukturelles Vektorautoregressionsmodell (SVAR), um Unsicherheits- und Finanzmarktschocks voneinander zu isolieren, ohne dabei den Einfluss dieser Schocks auf die Verbraucherpreise zu restringieren. Somit ermöglicht der Ansatz empirische Evidenz zur weitestgehend theoretischen Debatte über die Preiseffekte von Unsicherheits- und Finanzmarktschocks beizutragen. Darüber hinaus werden im Rahmen des SVAR Modells Erkenntnisse aus der jüngeren Forschungsliteratur berücksichtigt, welche die Bedeutung einer gemeinsamen Modellierung dieser beiden Störgrößen betonen. Das SVAR-Modell wird auf Daten für die Vereinigten Staaten und den Euroraum angewendet.

Ergebnisse

Die Ergebnisse lassen sich wie folgt zusammenfassen. Zwar bestätigt sich die bedeutsame Rolle dieser Störgrößen für Fluktuationen in der gesamtwirtschaftlichen Aktivität in beiden Wirtschaftsräumen, die Reaktion von Verbraucherpreisen auf diese Schocks ist jedoch nicht eindeutig. Darüber hinaus legen die Ergebnisse nahe, dass die in empirischen Anwendungen häufig anzutreffende Restriktion eines Gleichlaufs von Bruttoinlandsprodukt und Preisen in Reaktion auf diese Störgrößen eine Unterzeichnung der geschätzten Rolle von Unsicherheits- und Finanzmarktschocks für die realwirtschaftliche Aktivität implizieren kann.

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To Sign or Not to Sign? On the Response of Prices to Financial and Uncertainty Shocks*

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Abstract

Based on SVAR models identified by sign restrictions, we estimate the macroeconomic effects of financial and uncertainty shocks in the euro area and the US, paying particular attention to their effects on prices. While our results confirm that such disturbances are important drivers of output fluctuations in both economies, we find the shock responses of consumer prices to be ambiguous. Moreover, restricting prices to co-moving with output can considerably attenuate the measured impact of financial and uncertainty shocks on real activity.

Keywords: Financial Shocks, Uncertainty Shocks, Sign Restrictions, Euro Area, United States

JEL classification: C11, C32, E32, E44

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1 Introduction

Although the macroeconomic effects of uncertainty and financial shocks have attracted significant attention in quantitative macroeconomics, the empirical evidence on the impact of these shocks on prices is still scarce. In this paper, we propose a sign-identified SVAR framework that allows us to disentangle uncertainty and financial shocks, while being agnostic about the effects that these disturbances have on prices. Thus, we are not only able to provide empirical evidence on the theoretical debate about the price effects of uncertainty and financial shocks, but also to account for recent findings stressing the importance of jointly modeling these disturbances (Alfaro, Bloom, and Lin, 2018). The SVAR model is applied to data for the United States and the euro area.

Our investigation is motivated by the observation that recent empirical applications on the basis of sign-identified structural vector autoregressive models (SVARs) tend to impose a negative price reaction in response to contractionary financial shocks (e.g. Gambetti and Musso, 2017; Furlanetto, Ravazzolo, and Sarferaz, 2018).[1] While this choice is backed by a number of theoretical contributions (see, for example, Cúrdia and Woodford, 2010; Ajello, 2016), the overall evidence derived from microfounded dynamic stochastic general equilibrium (DSGE) models turns out to be ambiguous. For instance, De Fiore and Tristani (2013) emphasize that negative financial disturbances may act as a cost-push by raising firms' financing costs, implying rising marginal costs and, thus, upward pressure on prices. Gilchrist, Schoenle, Sim, and Zakrajšek (2017), in turn, show that the interaction of financial frictions and customer markets can induce firms to raise mark-ups, and thus prices, in response to negative financial shocks.

In a similar vein, recent theoretical contributions suggest that the price reaction to uncertainty shocks may also be far from clear-cut. Despite a range of studies reporting a co-movement of prices and output in response to uncertainty shocks (see Leduc and Liu, 2016; Cesa-Bianchi and Fernandez-Corugedo, 2018), Born and Pfeifer (2014), for example, state that firms in a sticky-price environment might find it optimal to raise prices in response to contractionary uncertainty shocks in order to avoid the risk of being stuck with prices that are too low. Furthermore, in a recent study, Fasani and Rossi (2018) provide theoretical results which indicate that, under a plausible specification of monetary policy, uncertainty shocks may drive output and prices in opposite directions.

Our main findings can be summarized as follows. First, we find that uncertainty and financial shocks play a prominent role for output fluctuations in both economies. Second, we confirm the theoretical ambiguity of price reactions to both types of disturbances. Further, we show that allowing prices to react freely to these shocks can have meaningful quantitative implications.

2 Empirical setup

Our analysis is based on quarterly VAR models with five lags for the United States and the euro area, estimated in (log) levels. The data sets used for the empirical analysis span the periods 1999:Q1–2017:Q2 for the euro area and 1986:Q3–2017:Q2 for the US. In

[1] One notable exception is the work by Abbate, Eickmeier, and Prieto (2016), who focus on the price response to financial shocks.

addition to the limitations of data availability, the choice of the respective start dates can also be motivated by economic considerations (launch of the euro area, Great Moderation period in the US).[2] The empirical model encompasses six variables; namely, data on gross domestic product (GDP), an index of consumer prices, a spread between the lending rate and government bond yields (bank spread), a shadow short rate (SSR) to measure the stance of the monetary policy[3], a proxy for macroeconomic uncertainty, and an indicator of financial market strains. Specifically, we measure macroeconomic uncertainty as the conditional volatility of the unforecastable components of a large set of time series, as proposed by Jurado, Ludvigson, and Ng (2015). For financial stress, we employ the credit spread indicator recently introduced by Gilchrist and Zakrajšek (2012).[4]

To identify the structural shocks, we implement sign restrictions following the approach of Rubio-Ramírez, Waggoner, and Zha (2010). Although the identification scheme presented in Table 1 is inspired by recent studies investigating the role of financial shocks for the business cycle, the present analysis differs from these studies in important ways: First, we identify both uncertainty and financial shocks. Second, we explicitly focus on the consequences of restricting price responses to these disturbances. Subsequently, we discuss the effects in terms of expansionary shocks, imposing restrictions on impact only.

Table 1: Sign restrictions

Restricted Version	Supply	Demand	MP	Financial	Uncertainty
LN(GDP)	+	+	+	+	+
LN(CPI)	-	+	+	+	+
SSR	-	+	-	+	+
BANK SPREAD		+		-	-
CREDIT RISK (CR)				-	-
CR / UNCERTAINTY				-	+
Unrestricted Version	Supply	Demand	MP	Financial	Uncertainty
LN(GDP)	+	+	+	+	+
LN(CPI)	-	+	+		
SSR	-	+	-	+	+
BANK SPREAD		+		-	-
CREDIT RISK (CR)				-	-
CR / UNCERTAINTY				-	+

Notes: A positive (negative) sign implies an on impact rise (decrease) in response to a shock. No sign implies that the on impact response is unrestricted.

The restrictions for aggregate demand, aggregate supply, and monetary policy shocks are consistent with characteristics of standard New Keynesian DSGE models. Specifically, it is assumed that expansionary demand shocks induce a rise in real GDP, the price index, and the policy rate, while supply disturbances move quantities and prices in the

[2] Employing Bayesian techniques, the reduced-form VAR models are estimated under a conjugate prior of the Normal-Inverse-Wishart form. The Supplementary Appendix presents more details about data sources and the estimation approach.

[3] The indicator is sourced from Krippner (2013).

[4] Meinen and Roehe (2017) and Gilchrist and Mojon (2018) provide the respective indicators for the euro area.

opposite direction. We also impose the restriction that the deflationary pressure caused by an expansionary supply shock leads to a reduction in the short-term rate. Positive monetary policy shocks increase output and prices, but imply a reduction in the interest rate. An expansionary financial shock is a disturbance that reduces financial market strains, macroeconomic uncertainty, and the bank spread, while it raises output, prices and the short-term rate. We follow, inter alia, Gambetti and Musso (2017) and disentangle financial from aggregate demand shocks by assuming that the latter are associated with an increase in the lending rate and, therefore, the bank spread. Based on a range of theoretical evidence, uncertainty shocks are assumed to resemble financial disturbances. In this respect, Bonciani and Van Roye (2016) show that – given some degree of stickiness in the lending rate – the spread between the lending rate and the risk-less rate decreases in response to an exogenous reduction in uncertainty.[5] Finally, following Furlanetto et al. (2018), we disentangle financial and uncertainty shocks by imposing the restriction that the former has a relatively stronger impact on the financial stress indicator than on uncertainty, which implies a decrease in the ratio of credit risk to uncertainty.[6] The opposite holds for the uncertainty shock which consequently causes the ratio to increase.[7] Even though Table 1 indicates that restrictions are imposed on the ratio of credit-risk-to-uncertainty, we note that each series is included separately in the VAR. This enables us to ensure that uncertainty and financial shocks do both, indeed, reduce uncertainty and financial stress on impact, reflecting recent evidence about their interdependence.[8]

The identification approach outlined above is contrasted with a model specification featuring no restrictions on the price response to financial and uncertainty shocks.[9] Relaxing the sign restriction of financial and uncertainty shocks on prices implies, however, that monetary policy reacts to these shocks even though there may be no need from the perspective of ensuring price stability. We point out that such a behavior is well in line with a broad-based approach of monetary policy authorities who, besides having price stability as an objective, also pursue the goal of financial stability, which might have been of particular relevance in the course of the financial crisis (e.g., Gilchrist and Zakrajšek, 2011; Gertler and Karadi, 2011). Specifically, our identification approach assumes that both financial and uncertainty shocks have an impact on credit spreads and output, calling for a monetary policy response. Note that this is in line with recent empirical evidence provided by Caldara and Herbst (2018), who document a direct and quantitatively significant reaction of monetary policy to changes in credit spreads. Moreover, by deliberately leaving the price reaction unrestricted, our specification can accommodate the optimal monetary policy response to negative financial shocks outlined in De Fiore and Tristani

[5] Note that in the model of Bonciani and Van Roye (2016) the lending rate itself (and not only the bank spread) also decreases in response to an expansionary uncertainty shock. In contrast, the empirical results by Grimme (2017) suggest that the lending rate increases, while the spread tends to decrease after an exogenous reduction in uncertainty. For this reason, we prefer to impose the sign restrictions on the spread.

[6] The rationale for disentangling financial and uncertainty shocks is reminiscent of the approach applied by Caldara, Fuentes-Albero, Gilchrist, and Zakrajŝek (2016).

[7] In order to be able to restrict the relative responses, both series are normalized to have the same first and second moments.

[8] We also impose signs on the residual shock to ensure that it does not act like any other structural disturbance in the system.

[9] As regards the identification of a financial shock, such a strategy has also been followed by Mandler and Scharnagl (2018).

(2013), which is to lower the policy rate in the face of adverse financial market conditions, despite inflationary pressure stemming from firms' pass-through of increased financing costs.

3 Results

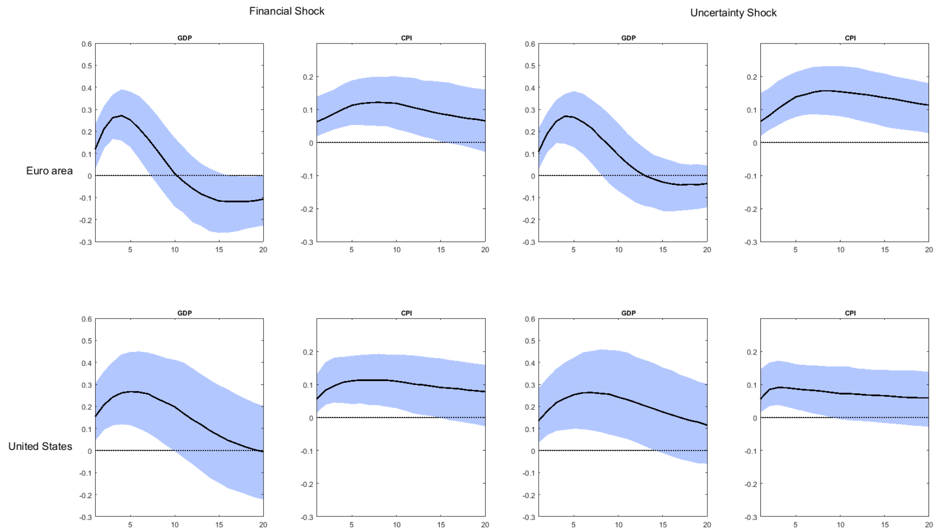
Figure 1 presents impulse responses.[10] The upper panel, which refers to results with restricted price responses, suggests that financial and uncertainty disturbances significantly impact GDP. For the US, the effects of uncertainty shocks tend to be particularly persistent, which is in line with findings by Jurado et al. (2015), for example. Moreover, prices increase modestly, though significantly, after financial and uncertainty shocks. Turning to results with unrestricted price responses in the lower panel, some differences become apparent. For the euro area, these differences are modest in that we obtain more variation in the price response, while the IRFs remain above zero on impact. In contrast, in case of the US, there is not only more variability in the price responses, but the median price response is even partly negative on impact. Even though there is a lot of uncertainty around these estimates, implying that they usually cannot be distinguished from zero on impact, these results do support the notion that the reaction of prices to both financial and uncertainty shocks is ambiguous. In order to capture rather broad types of financial and uncertainty shocks, it therefore appears appropriate to leave the price response unrestricted.

This view is further backed up by the results presented in Table 2, which contains forecast error variance decompositions (FEVDs), indicating the relative contribution of each shock to explaining variations in aggregate output. According to these numbers, financial and uncertainty shocks can account for a substantial part of output variation in both regions. At first glance, this observation is independent of the price restriction on these shocks. However, allowing prices to adjust freely in response to these disturbances leads to these shocks making larger contributions to output variation, especially, in the US. Note that this result does not necessarily require a separation of uncertainty and financial shocks, but also holds when considering the combined effect of these disturbances.

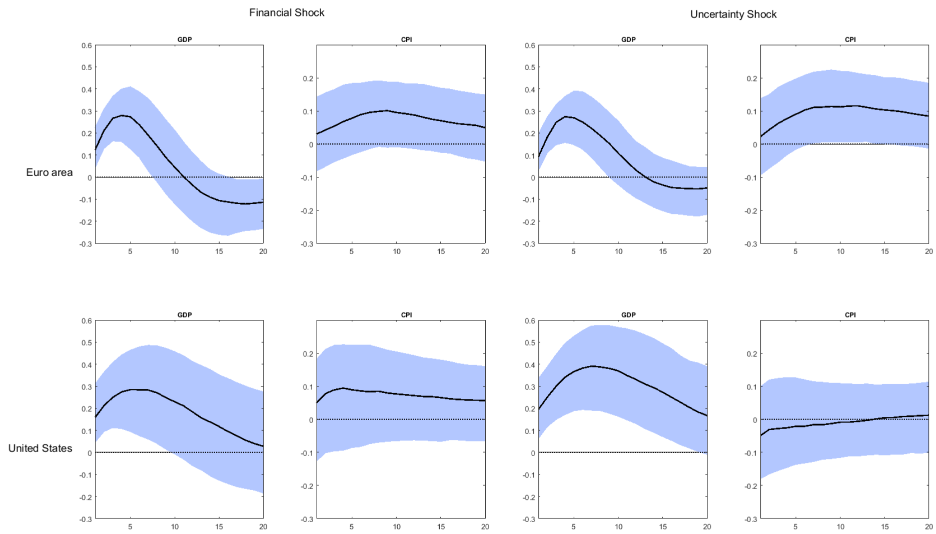
[10] In this paper, we follow the bulk of the empirical literature and discuss results referring to the point-wise median. In a supplementary Appendix, we also present results consistent with the median-target model (see Fry and Pagan, 2011). Moreover, the Appendix contains results based on a sub-sample restricted to the 'pre-crisis' period and on an alternative identification strategy.

Figure 1: GDP and price responses to financial and uncertainty shocks

Restricted price response



Unrestricted price response



Notes: IRFs (in percent) of GDP and CPI to financial and uncertainty shocks of one standard deviation. Solid lines depict median responses. Shaded areas indicate 68% posterior probability regions.

Table 2: Contribution of financial and uncertainty shocks to GDP fluctuations

		Restricted price response				Unrestricted price response			
		1	4	12	20	1	4	12	20
EA	Financial shock	0.14	0.30	0.20	0.24	0.15	0.31	0.24	0.24
	Uncertainty shock	0.11	0.28	0.22	0.18	0.08	0.28	0.23	0.20
US	Financial shock	0.14	0.21	0.15	0.13	0.16	0.23	0.19	0.15
	Uncertainty shock	0.11	0.15	0.15	0.12	0.24	0.35	0.36	0.31

Notes: The table presents the FEVDs of GDP with respect to financial and uncertainty shocks. The individual contributions refer to the point-wise median and are re-scaled so that they sum to one.

4 Conclusion

Our empirical results have three main implications. First, both financial and uncertainty shocks matter for real economic activity. Second, the response of prices is ambiguous with respect to these shocks. Third, constraining prices to co-moving with output can imply underestimating the role of financial and uncertainty shocks for real activity.

A Appendix

This appendix contains additional information about the paper "To Sign or Not to Sign? On the Response of Prices to Financial and Uncertainty Shocks". First, we detail the estimation approach. Second, we set out data sources and explain our choices for selecting certain indicators. Third, additional estimation results are presented.

A.1 Estimation details

Our analysis is based on quarterly VAR models with $p = 5$ lags and q endogenous variables for the euro area and the United States, estimated in (log) levels:

$$y_t = \tilde{c} + B_1 y_{t-1} + \ldots + B_p y_{t-p} + u_t \quad (1)$$
$$u_t \sim N(0, \Sigma), \quad (2)$$

where y_t denotes a $q \times 1$ vector of endogenous variables, u_t a $q \times 1$ vector of errors, and $\tilde{c}, B_1, \ldots, B_p$, and Σ represent matrices of suitable dimensions containing the unknown parameters of the model, including the constants ($\tilde{c}$), coefficients of lagged endogenous variables ($B_1, \ldots, B_p$), and the covariance matrix (Σ). The reduced-form VAR model is estimated employing Bayesian techniques. Specifically, we use a Normal-Inverse-Wishart prior, assuming that $\beta \equiv vec(c, B_1 \ldots, B_p)$ is normally distributed and that Σ has an inverse Wishart distribution with scale S and ν degrees of freedom:

$$\beta \sim N(b, \Sigma \otimes \bar{H}) \quad (3)$$
$$\Sigma \sim IW(S, \nu). \quad (4)$$

The prior for β is of the Minnesota-type.[11] Specifically, let i refer to the dependent variable in the ith equation, j to the independent variable in that equation, and l to the lag number. We then assume that the prior distribution for β is defined such that $E[(B_l)_{ij}] = 0.8$ for $i = j$ and $l = 1$ and 0 otherwise, while all other elements in b are set to zero. The diagonal elements of the diagonal matrix $\bar{H}$ are defined as $\left(\frac{\lambda_1}{\sigma_i l^{\lambda_2}}\right)^2$ for coefficients on lags and $(\lambda_1 \lambda_3)^2$ for the constant. The prior parameters σ are specified using ordinary least squares (OLS) estimates of univariate AR(1) models. More specifically, σ_i denotes the standard deviations of error terms from the OLS regressions. The hyperparameters λ_1, λ_2, and λ_3 are set in accordance with standard values commonly used in the literature.[12] Turning to the inverse Wishart distribution, the degrees of freedom ν amount to $T+q+1$, with T denoting the sample length. The scale parameter S is a $q \times q$ diagonal matrix with diagonal elements σ_i^2.

Letting A_0 summarize the contemporaneous relations between the elements of y_t, the structural representation of the VAR model (1) can be expressed as

$$A_0 y_t = c + A_1 y_{t-1} + \ldots + A_p y_{t-p} + \epsilon_t, \quad (5)$$

[11] We use a Minnesota-type prior for the coefficient matrix to prevent running into problems of "overfitting", which is especially relevant when using the data for the euro area.

[12] Specifically, we set hyperparameters $\lambda_1 = 0.1$, $\lambda_2 = 1$, and $\lambda_3 = 10^5$.

with $\epsilon \sim N(0, I)$, where I refers to the identity matrix. Since the reduced-form representation of the SVAR is derived by pre-multiplying expression (5) with A_0^{-1}, i.e.

$$\begin{aligned} A_0^{-1}A_0 y_t &= A_0^{-1}c + A_0^{-1}A_1 y_{t-1} + \ldots + A_0^{-1}A_p y_{t-p} + A_0^{-1}\epsilon_t && (6) \\ y_t &= \tilde{c} + B_1 y_{t-1} + \ldots + B_p y_{t-p} + u_t, && (7) \end{aligned}$$

identifying the structural parameters of the model boils down to finding the appropriate matrix $\tilde{A} = A_0^{-1}$. In this study, this is done by means of sign restrictions, following the strategy outlined by Rubio-Ramírez et al. (2010).[13] The approach exploits the fact that $\Sigma = P'P$, where the lower triangular matrix P' is the Cholesky decomposition of Σ. Moreover, we define Q' to be an orthonormal matrix such that $Q'Q = I$. Q is obtained by applying the QR decomposition to a random matrix D drawn from an independent standard normal distribution (i.e., $D = QR$, where the diagonal of the upper triangular matrix R is normalized to be positive). It follows that $\Sigma = \tilde{A}\tilde{A}' = P'Q'QP$. In particular, $\tilde{A} = P'Q'$ is considered as a solution to the identification problem if the impulse responses implied by Q' satisfy a set of sign restrictions. In practice, for each of the 500 draws sampled from the posterior distribution, we proceed with generating random matrices Q' until $P'Q'$ accords with the imposed sign restrictions. The sign restrictions implied by the identification schemes are discussed in section 2 of the main text.

A.2 Data details

The data sets used for the empirical analysis span the periods 1999:Q1–2017:Q2 for the euro area and 1986:Q3–2017:Q2 for the US. Our main empirical model encompasses six variables. In particular, we employ data on gross domestic product (GDP), an index of consumer prices, a shadow short rate (SSR) to measure the stance of the monetary policy[14], a proxy for macroeconomic uncertainty, and an indicator of financial market strains. As regards the sample length, the choice of the respective start dates is primarily due to limitations of data availability. This holds in particular for the financial stress indicator provided by Gilchrist and Mojon (2018), which is not not available before 1999. In addition, the start date can also be motivated by economic considerations, since the 1999 constitutes the year of the launch of the euro. For the US, the lending rate used in this study is not available before the third quarter in 1986. This starting date also appears reasonable in light of evidence on the Great Moderation, which suggests a structural shift of the economy towards a less volatile regime (see, for example, McConnell and Perez-Quiros, 2000; Arias, Hansen, and Ohanian, 2007; Justiniano and Primiceri, 2008), and the break in the policy conduct with the advent of Paul Volcker as Fed's chairman (see, for example, Clarida, Galí, and Gertler, 2000; Lubik and Schorfheide, 2004; Benati and Surico, 2009; Castelnuovo and Fanelli, 2015). As depicted in Table A.1, most of the time series are drawn from standard sources. One exception involves the shadow short rate, which is obtained from Krippner (2013). Moreover, the measures of uncertainty and financial stress deserve some more detailed consideration.

[13] Note that we deliberately impose the signs on impact only. For instance, Gambetti and Musso (2017) emphasize that such a strategy is more robust than setting restrictions for longer time horizons.

[14] Following Krippner (2013), the shadow short rate (SSR) seeks to measure the accommodation in monetary policy when the short rate is at the zero lower bound (ZLB).

Due to the absence of an objective measure, a range of uncertainty proxies has been proposed in the empirical literature.[15] What is more, the relevance of uncertainty as a driver of real economic activity can vary substantially across these indicators (e.g., Meinen and Roehe, 2017). While the bulk of the evidence for the latter finding is based on recursively identified VAR models, Caldara et al. (2016) document that this variability of results can also be present in models identified by alternative means, such as a penalty function approach. In this respect, a number of recent studies have highlighted the fact that the measure of time-varying macroeconomic uncertainty proposed by Jurado et al. (2015) stands out in featuring several desirable properties, from both a theoretical and an empirical perspective (see Caldara et al., 2016; Born and Pfeifer, 2017). First, the indicator is closely related to a typical definition of uncertainty as the purely unforecastable component of future values of macroeconomic indicators given the information set available to an economic decision maker. Second, the indicator stands out in being based on a broad information set. We therefore rely on this measure of uncertainty in the current paper. For the US, the indicator is obtained from Jurado et al. (2015), while Meinen and Roehe (2017) provide this proxy for the four largest euro-area economies (Germany, France, Italy, and Spain).[16] A measure for the euro area as a whole is derived by computing the average of the country-specific indicators.

As regards the measurement of financial stress, Gilchrist and Zakrajšek (2012) recently introduced a credit spread indicator, which turns out to have considerable predictive power for economic activity. The indicator is obtained by aggregating information about prices of individual corporate bonds and can be further decomposed to derive the excess bond premium which is a measure of credit spreads net of an estimated default risk.[17] While both Caldara et al. (2016) and Furlanetto et al. (2018) use this latter measure when assessing the role of financial factors in the US business cycle, we rely on the overall credit risk indicator, since it is available not only for the US, but also for the euro area (see Gilchrist and Mojon, 2018). In this regard, it is important to note that the overall credit spread indicator and the excess bond premium display a significant degree of comovement in the US during the period under investigation, amounting to a correlation coefficient of 0.78 at a monthly frequency.

Table A.1 presents details of the data used for the empirical analysis. The table also contains information about investment and stock price series for both economies, which are used in robustness checks below.

[15] Well-known examples include indicators based on the realized or implied volatility of stock market returns (Bloom, 2009), economic policy uncertainty derived from newspaper article counts (Baker, Bloom, and Davis, 2016), measures based on the dispersion in firms' subjective expectations using business climate surveys (Bachmann, Elstner, and Sims, 2013), indicators of macroeconomic uncertainty that are based on the unpredictable components of a broad set of economic variables as in (Jurado et al., 2015; Rossi and Sekhposyan, 2015), and ex-post evaluations of forecasts (Scotti, 2016).

[16] In either case, we consider uncertainty indicators referring to the three months ahead forecast horizon.

[17] Thus, this indicator may be interpreted as measuring the extra compensation – in addition to that for expected losses – that bond holders demand for the exposure to US non-financial corporate credit risk.

A.3 Additional results

In this section, we present additional estimation results. First, we present results referring to the median-target model. Second, we restrict the estimation samples to the pre-crisis period. Third, we consider an alternative identification scheme, which was recently proposed by Furlanetto et al. (2018), in order to assess the robustness of our findings with the respect to the identification assumptions. As regards the two latter exercises, we focus our attention on sign restrictions which allow prices to respond freely to financial and uncertainty shocks.

A.3.1 Median-target model

VAR models identified by sign restrictions produce a set of admissible models. The applied literature follows alternative ways of presenting the dynamic properties of the estimated model usually summarized by impulse response functions, forecast error variance decomposition, and historical decompositions. The most common approach is to compute the point-wise median (see Uhlig, 2005, for an early example). Indeed, most of the studies we relate to in the main paper adopt this approach. In this respect, Fry and Pagan (2011) point out that the median impulse response likely combines information about shocks stemming from different models, rendering a structural interpretation problematic. Instead, they propose choosing the model that is closest to the median response, which they term median-target model. As in the main text, in this appendix, we follow the bulk of the applied literature and present results referring to the point-wise median. Additionally, we also show results in accordance with the approach by Fry and Pagan (2011). Table A.2 presents the forecast error variance decomposition (FEVD) of GDP, referring to both the point-wise median (as already shown in the main text) and the median-target model.

A.3.2 Excluding the financial crisis period

The financial crisis was characterized by significant spikes in macroeconomic uncertainty and financial market strains. In this subsection, we therefore investigate whether our main findings are driven by developments during this period of time. To this end, we re-estimate our model, while restricting the estimation samples to the pre-crisis period. In particular, the estimation sample terminates in the second quarter of 2007. Note that we perform this sensitivity check only for the US, given that the sample for the euro area does not start before 1999.

The estimation results are presented in Table A.3. The results do not suggest that the findings from the main text are due solely to the financial crisis. In particular, even when excluding the crisis from the estimation sample, we find that financial and uncertainty shocks are important drivers of fluctuations in US GDP.

A.3.3 Alternative identification scheme

In this subsection, we present estimation results based on an identification scheme in accordance with Furlanetto et al. (2018). Our application differs from their approach in that we include a monetary policy shock instead of disentangling financial disturbances into credit and housing shocks. Moreover, in line with our findings from the main text, we do not restrict the price response to uncertainty and financial shocks.

Restrictions for aggregate demand, supply, and monetary policy shocks are consistent with signs described in the main text. The main difference with respect to our baseline identification scheme relates to the separation of demand disturbances from financial shocks. In particular, Furlanetto et al. (2018) propose disentangling demand from financial factors by including data on investment in their reduced-form VAR. Thus, an additional shock, namely an investment-specific disturbance, is identified. This disturbance is separated from the demand shock by assuming that the latter affects non-investment-related output components relatively more strongly, which implies a decrease in the ratio of investment to output. By contrast, investment-specific disturbances move gross capital formation (GFC) comparatively more strongly, so that its ratio to GDP rises.[18] Note that investment-specific shocks behave like demand shocks in the sense that they imply a co-movement of output and consumer prices as well as a respective monetary policy reaction.

A financial shock is also assumed to cause an investment boom and, thus, to affect GFC relatively more strongly than other output components. This disturbance is separated from the investment-specific shock by including a stock market indicator in the model. By referring to Christiano, Motto, and Rostagno (2014), it is argued that investment-specific disturbances represent shocks to the supply of capital, so that they are characterized by an increase in the stock of capital, entailing a rise in investment and output and a decrease in the price of capital, which implies a fall in stock prices.[19] On the other hand, financial shocks act like shocks to the demand for capital, implying a positive relationship between output and the stock of capital in combination with an increase in stock prices.[20] Financial shocks thus positively affect output, investment, and stock prices, while they imply a reduction in credit risk and uncertainty. Even though prices are allowed to respond freely to financial shocks we assume, for reasons described in the main text, a positive monetary policy response in accordance with the changes in output and financial stress. Finally, uncertainty shocks are assumed to behave like financial shocks. As outlined above, the two disturbances are disentangled by restricting the relative responses of financial stress and uncertainty indicators.

Table A.4 presents an overview of the set of sign restrictions. As before, we note that we include each series separately in the VAR, even though restrictions are imposed on the ratio of investment-to-output and credit-risk-to-uncertainty.

Table A.5 presents the forecast error variance decompositions for the shocks of interest.

[18] As noted by Furlanetto et al. (2018), the identified aggregate demand shock thus tends to mirror a 'non-investment specific' demand shock. They further note that such a shock is also in line with standard DSGE models and, importantly, that it can accommodate both crowding-out and crowding-in of investment after a demand shock.

[19] It is assumed that the price of capital is directly related to a firm's stock market value and that it is a key factor in a firm's net worth. Although this approach represents an elegant way of disentangling financial shocks from demand disturbances, it relies on the assumption of a negative stock market response to an expansionary investment-specific shock.

[20] Furlanetto et al. (2018) emphasize that the considered financial shock is consistent with a broad set of DSGE models. Hence, it accommodates a variety of potential causes of financial shocks, without the need to be specific about the exact channel. For instance, the financial shock may be related to loan supply effects (caused, for example, by improvements in banks' net worth); or to improved access of firms to bond financing; or to shocks originating in the housing sector. However, the authors also note that their identified financial disturbance cannot accommodate financial factors that move output and prices in opposite directions. We therefore extend the proposed identification scheme in this regard.

Note that we reduce the number of draws to 200 for this exercise since the computational burden is substantially higher when applying these sign restrictions. The results for the point-wise median are remarkably similar to those presented in the main text, suggesting that our main results are not primarily driven by the chosen identification scheme. This also holds for the median target model in the case of the US.

Table A.1: Data description and sources

Indicator	Description	Source	Code
Data for the euro area			
Real GDP	chain-linked; sa	HAVER	J025GDPT@EUDATA
Price Index	harmonized index of consumer prices; sa	HAVER	H025H@EUDATA
Real Investment	gross fixed capital formation; sa	HAVER	J025IFT@EUDATA
Stock Price Index	EURO STOXX 50 Price Index; sa*	HAVER	sa(S023T5U@EUDATA)
Safe bond	estimated 10-year government debt yield (Germany)	HAVER	DENTA@GERMANY
Lending Rate	Euro area annualized agreed rate; after 1999	ECB data warehouse	MIR:M:U2:B:A2A:A:R:A:2240:EUR:N
	Euro area annualized agreed rate; before 2000	ECB data warehouse	MIR:M:I2:B:A2A:A:R:A:2240:EUR:N
SSR	Shadow short rate	Online	https://www.rbnz.govt.nz/research-and-publications/research-programme/additional-research/measures-of-the-stance-of-united-states-monetary-policy/comparison-of-international-monetary-policy-measures
Credit Risk Indicator	Spreads by Gilchrist and Mojon (2017)	Online	https://publications.banque-france.fr/en/economic-and-financial-publications-working-papers/credit-risk-euro-area
Uncertainty Indicator	Macro uncertainty by Meinen and Roehe (2017) (average for DE, ES, FR, IT)	Available from the authors	
Data for the US			
Real GDP	chain-linked, annualized; sa	HAVER	GDPH@USECON
Price Index	personal consumption expenditure; sa	HAVER	JC@USECON
Real Investment	gross private domestic investment, chain-linked, annualized; sa	HAVER	IH@USECON
Stock Price Index	Standard & Poor's 500 composite; sa*	HAVER	sa(SP500@USECON)
Lending Rate	C&I loan rate spread over intended fed funds rate: all loans, actual DISC (%)	HAVER	FCIRS@USECON plus
	plus intended federal funds rate DISC (%)	HAVER	FFTRR@USECON
Safe bond	10-year treasury note yield at constant maturity	HAVER	FCM10@USECON
SSR	Shadow short rate by Leo Krippner	Online	https://www.rbnz.govt.nz/research-and-publications/research-programme/additional-research/measures-of-the-stance-of-united-states-monetary-policy
Credit Risk Indicator	Spreads by Gilchrist and Zakrajšek (2012)	Online	https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/files/ebp_csv.csv
Uncertainty Indicator	Macro uncertainty by Jurado et al. (2015)	Online	https://www.sydneyludvigson.com/data-and-appendixes/

* indicates seasonal adjustment by applying a X-12-ARIMA filter.

Table A.2: Contribution of financial and uncertainty shocks to GDP fluctuations

		Restricted price response				Unrestricted price response			
		1	4	12	20	1	4	12	20
Point-wise median									
EA	Financial shock	0.14	0.30	0.20	0.24	0.15	0.31	0.24	0.24
	Uncertainty shock	0.11	0.28	0.22	0.18	0.08	0.28	0.23	0.20
US	Financial shock	0.14	0.21	0.15	0.13	0.16	0.23	0.19	0.15
	Uncertainty shock	0.11	0.15	0.15	0.12	0.24	0.35	0.36	0.31
Median-target									
EA	Financial shock	0.08	0.33	0.23	0.24	0.21	0.45	0.48	0.43
	Uncertainty shock	0.01	0.04	0.03	0.03	0.06	0.22	0.28	0.26
US	Financial shock	0.19	0.19	0.15	0.12	0.26	0.33	0.31	0.30
	Uncertainty shock	0.05	0.08	0.12	0.11	0.06	0.17	0.26	0.22

Notes: The table presents the FEVDs of GDP with respect to financial and uncertainty shocks. The individual contributions are re-scaled so that they sum to one whenever the FEVD refers to the point-wise median.

Table A.3: Contribution of financial and uncertainty shocks to GDP fluctuations, when excluding the crisis period

		1	4	12	20
Point-wise median					
US	Financial shock	0.23	0.26	0.19	0.17
	Uncertainty shock	0.21	0.22	0.20	0.16
Median-target					
US	Financial shock	0.20	0.19	0.18	0.17
	Uncertainty shock	0.46	0.47	0.39	0.34

Notes: The table presents the FEVDs of GDP with respect to financial and uncertainty shocks. The individual contributions are re-scaled so that they sum to one whenever the FEVD refers to the point-wise median.

Table A.4: Sign restrictions - alternative identification scheme

	Supply	Demand	MP	Investment	Financial	Uncertainty
LN(GDP)	+	+	+	+	+	+
LN(PPI)	-	+	+	+		
SSR	-	+	-	+	+	+
LN(GCF)-LN(GDP)		-		+	+	+
LN(STOCK)				-	+	+
CREDIT RISK (CR)					-	-
CR / UNCERTAINTY					-	+

Notes: A positive (negative) sign implies an on impact rise (decrease) in response to a shock. No sign implies that the on impact response is unrestricted.

Table A.5: Contribution of financial and uncertainty shocks to GDP fluctuations, using the alternative identification scheme

		1	4	12	20
Point-wise median					
EA	Financial shock	0.17	0.26	0.21	0.21
	Uncertainty shock	0.15	0.25	0.21	0.17
US	Financial shock	0.16	0.25	0.20	0.17
	Uncertainty shock	0.27	0.37	0.38	0.33
Median-target					
EA	Financial shock	0.01	0.06	0.06	0.15
	Uncertainty shock	0.42	0.67	0.62	0.51
US	Financial shock	0.24	0.34	0.25	0.20
	Uncertainty shock	0.04	0.20	0.25	0.24

Notes: The table presents the FEVDs of GDP with respect to financial and uncertainty shocks. In accordance with Furlanetto et al. (2018), we re-scale the individual contributions so that they sum to one whenever the FEVD refers to the point-wise median.

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