European Economic Review 136 (2021) 103750

Contents lists available at ScienceDirect

European Economic Review

journal homepage: www.elsevier.com/locate/euroecorev

Financial uncertainty and real activity: The good, the bad, and the ugly[☆]

Giovanni Caggiano[a,b], Efrem Castelnuovo[b,c,*], Silvia Delrio[d], Richard Kima[a]

[a] Monash University, Australia
[b] University of Padova, Italy
[c] University of Melbourne, Australia
[d] Bank of Italy, Italy

ARTICLE INFO

Article history:
Received 10 July 2020
Revised 2 February 2021
Accepted 20 April 2021
Available online 30 April 2021

JEL classification:
C32
E32

Keywords:
Uncertainty shocks
Finance-uncertainty multiplier
Set-identification
VAR
Credit supply disruptions
Financial frictions

ABSTRACT

This paper quantifies the finance uncertainty multiplier (i.e., the magnifying effect of the real impact of uncertainty shocks due to credit frictions) by relying on two historical events related to the US economy, i.e., the large jump in financial uncertainty occurred in October 1987 (which was not accompanied by a deterioration of the credit supply conditions), and the comparable jump in financial uncertainty in September 2008 (which went hand-in-hand with an increase in financial stress). Working with a VAR framework and a set-identification strategy that focuses on - but it is not limited to - restrictions related to these two dates, we estimate the finance uncertainty multiplier to be around 2, i.e., credit supply disruptions are found to double the negative output response to an uncertainty shock. An exercise with employment as an indicator of the business cycle returns a finance uncertainty multiplier of about 1.5, i.e., lower but still sizeable.

1. Introduction

The COVID-19 shock that forcefully hit the US economy in March 2020 injected a level of uncertainty in financial markets comparable to, if not higher than, the one associated with the 2007-09 Great Recession and, before that, to the Black Monday (Baker et al., 2020). This is bad news. A large increase in uncertainty was most likely one of the relevant drivers of the US Great Recession (Bloom, 2014; Basu and Bundick, 2017; Benati, 2019; Pellegrino et al., 2020). A connected strand of the literature stresses the role played by the toxic "high uncertainty-high credit stress" tandem.[1] Had the credit market functioned in a business-as-usual fashion in 2007-09, the output loss experienced by the US economy because of the

☆ We thank Florin Bilbiie (Editor), two anonymous referees, and in particular Luca Benati (Associate Editor) for their thoughtful comments and suggestions. We also thank Marco Brianti, Renée Fry-McKibbin, Luca Fanelli, Laurent Ferrara, Martin Fukac, Benoit Mojon, James Morley, Giovanni Pellegrino, Tim Robinson, Rodney Strachan, Kerem Tuzcuoglu, and participants to various conferences, workshops, seminars, and webinars for valuable suggestions. Financial support by the Australian Research Council via the DP160102281, DP160102654, and DP190102802 is gratefully acknowledged. The views expressed in this paper are those of the authors and do not involve the responsibility of the Bank of Italy.

* Corresponding author.
E-mail address: efrem.castelnuovo@unipd.it (E. Castelnuovo).

[1] See Gertler and Gilchrist (2017) for an analysis of credit (and, more in general, financial) market disruptions in the US during the Great Recession, and (Bloom, 2014) and (Castelnuovo, 2019) for contributions on the business cycle effects of uncertainty shocks.

https://doi.org/10.1016/j.euroecorev.2021.103750
0014-2921/

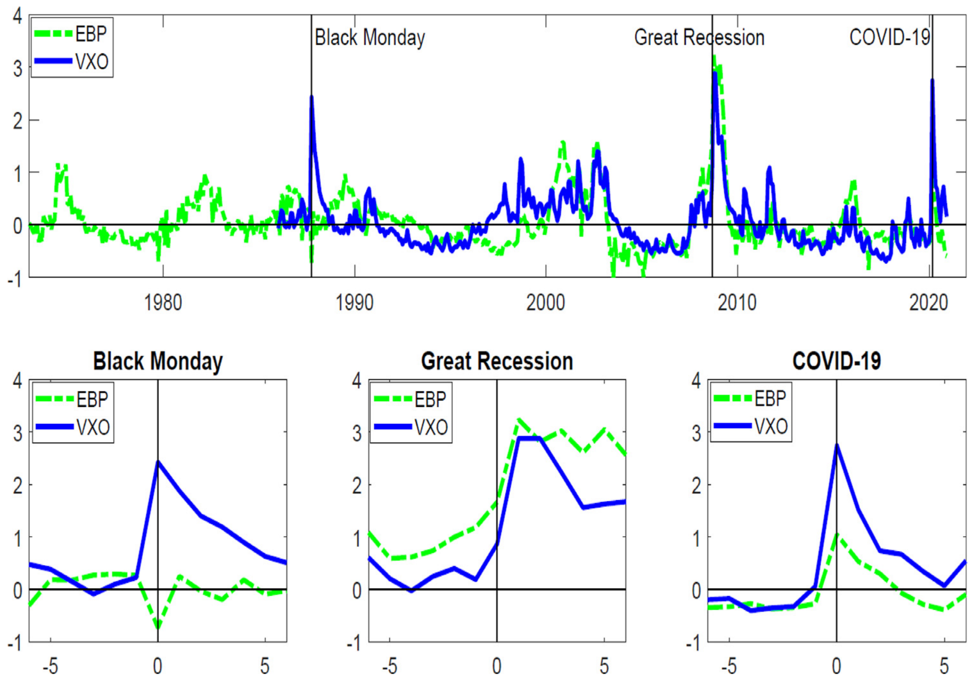

Fig. 1. Financial stress and uncertainty in 1987, 2008, 2020. Top panel: VXO and Excess Bond Premium. Bottom panel: VXO and EBP right before/after October 1987 (left), September 2008 (middle), March 2020 (right). Excess Bond Premium as in Gilchrist and Zakrajšek (2012), updated by Favara et al. (2016).

increase in uncertainty would have likely been substantially lower. Broadly referring to financial conditions, (Alfaro et al., 2019) coin the term "finance uncertainty multiplier" (FUM) to indicate the role played by financial frictions in magnifying the real effects of uncertainty shocks.

How large is the FUM? Addressing this question is crucial for policymakers. If the FUM is large, liquidity injections following shocks associated with spikes in uncertainty are the most obvious policy move to avoid repeating another Great Recession. Differently, if the financial multiplier is small, rapid interventions to kill uncertainty (via clear and credible communication of future policy moves, e.g., forward guidance policies, or the quick development of a testing, tracing, and treating plan for pandemics like COVID-19) should come first in policymakers' agendas.[2] Unfortunately, separately identifying the impact of spikes in uncertainty and the role of credit frictions in the data is a formidable challenge in applied work (Stock and Watson, 2012). Fig. 1 explains why. The Figure shows the evolution of the VXO, a proxy of financial uncertainty, and that of the excess bond premium (a proxy for credit supply disruptions proposed by Gilchrist and Zakrajšek (2012), EBP hereafter) over the last five decades.[3] Financial volatility displays three distinct peaks, i.e., the Black Monday one, the one occurred during the Great Recession, and the recent COVID-19 one. The toxic uncertainty-credit stress tandem occurred during the Great Recession - a *bad* economic outcome - is evident in the data. This correlation is the reason why separating first and second-moment financial shocks is complicated. A qualitatively similar pattern, due to the COVID-19 shock, was starting to take place in March 2020, but prompt and massive fiscal and monetary policy interventions successfully contained credit supply disruptions, whose materialization would have probably led to an even *uglier* economic outcome.[4] Intriguingly, the Black Monday episode in October 1987 was characterized by high financial volatility but *low* credit stress, and no recession took place - *good* outcome. Hence, the Black Monday potentially offers different information with respect to the one associated with the Great Recession (and, to some extent, COVID-19). Can the joint investigation of the Black Monday and the Great Recession help us separately identify the role of uncertainty shocks and that of credit supply disruptions? If so, can we estimate the FUM for the US with aggregate time series data?

[2] For evidence in favor of the correlation between the VIX and the growth rate of new COVID-19 cases, see https://www.sifma.org/resources/news/podcast-vix-and-the-virus/.

[3] The excess bond premium, estimated by Gilchrist and Zakrajšek (2012), is the component of corporate bond credit spreads that is not directly attributable to expected default risk.

[4] A detailed list of macroeconomic policy responses by the US (as well as a variety of other countries) can be found here: https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19.

This paper addresses these questions via a time-series VAR analysis based on: i) state-of-the-art measures of financial uncertainty and credit stress, respectively estimated by Ludvigson et al. (2019) and Gilchrist and Zakrajšek (2012);[5] ii) restrictions designed to achieve set-identification, i.e., identification of models consistent with the data and in line with reasonable economic a-priori on the features of uncertainty and financial shocks in the scrutinized post-WWII US sample. We achieve separate identification of the first moment (credit supply) and second moment (financial uncertainty) shocks by imposing narrative restrictions based on events occurred in October 1987 and September and October 2008 on top of traditional sign restrictions (Faust, 1998; Canova and de Nicoló, 2002; Uhlig, 2005) and ratio restrictions (Peersman, 2005; Furlanetto et al., 2019). As stressed above, the Black Monday and the Great Recession featured a very different correlation between credit supply disruptions and financial uncertainty. While different realizations of such a correlation are likely related to different interpretative stories, a common feature in these two different historical periods is that credit supply shocks and financial uncertainty shocks likely played a major role in driving the unexpected components of these variables' realizations. Consequently, we require our structural VAR model to assign to financial uncertainty (credit supply) shocks the role of the most relevant driver of the forecast error of uncertainty (excess bond premium) in such dates. This identification strategy, first proposed by Antolín-Díaz and Rubio-Ramírez (2019) and applied to the identification of oil and monetary policy shocks, turns out to be very powerful in selecting out models that do not well represent the 1987 and 2008 episodes.[6]

Our findings are the following. A financial uncertainty shock induces a temporary but persistent increase in EBP and macroeconomic uncertainty, and a decrease in real activity, the stock market, and the policy rate. We document qualitatively similar macroeconomic responses to an EBP shock, which also increases financial uncertainty. Both shocks are found to be relevant drivers of the business cycle in normal times (i.e., on average), with a contribution to the volatility of real GDP of about 16% (financial uncertainty shock) and 17% (credit supply shock). The contribution of these shocks is found to be much larger when it comes to explaining the fall in output during the Great Recession, with the combination of the two shocks being responsible for about 70% of the fall in output in June 2009 (the end of the recession according to the National Bureau of Economic Research). Turning to the main finding of this paper, a counterfactual exercise designed to quantify the size of the finance uncertainty multiplier - in which we ask our model what would have happened to real activity after a financial uncertainty shock if the response of EBP had been muted - points to a dramatically milder response of real GDP compared with the "factual" one, i.e., the one allowing for the endogenous response of EBP to the shock. Such a comparison points to a finance uncertainty multiplier equal around 2, i.e., the endogenous response of EBP doubles the response of real GDP to a financial uncertainty shock. This figure, obtained with a time-series approach, matches the one put forth by Alfaro et al. (2019), who work with a micro-founded model of the business cycle estimated with micro data. Going back to the policy implications discussed above, our findings support rapid and massive policy interventions aiming at keeping the cost of credit in line with normal times.

The structure of the paper is the following. Section 2 discusses some related literature. Section 3 offers details on our empirical specification, with emphasis on our identification strategy. Section 4 documents our empirical results. Section 5 focuses on the quantification of the finance uncertainty multiplier. Section 6 concludes.

2. Related literature

We connect to various contributions that have recently looked at the business cycle effects of uncertainty, financial frictions, and financial shocks. Caldara et al. (2016) employ a linear VAR to study the macroeconomic effects of uncertainty shocks and those of first-moment financial shocks. They work with a penalty function approach to disentangle first and second moment financial disturbances based on their impact on the impulse responses of the corresponding financial proxies used in the VAR. They find uncertainty shocks to have an especially negative economic impact when they materialize in correspondence of a tightening of financial conditions. Lhuissier and Tripier (2016), Popp and Zhang (2016), and Alessandri and Mumtaz (2019) employ nonlinear VAR frameworks to deal with the uncertainty shocks-financial frictions interaction. They find that uncertainty has a larger negative effect on output in periods of financial distress than in tranquil times. We build on these contributions by working with informative restrictions for the identification of financial uncertainty shocks that do not require to deal with a recursive representation of the economic system. In this sense, our paper is close to the one by Furlanetto et al. (2019), who identify financial and uncertainty shocks using a sign restrictions approach which features, among others, restrictions on ratios of proxies for first and second moment financial indicators. Our identification scheme borrows this idea from them, as well as event restrictions à la (Antolín-Díaz and Rubio-Ramírez, 2019) identified by our reading of analysis on the Black Monday and the Great Recession. Related papers are Redl (2020), who identifies uncertainty shocks via the imposition of restrictions on the sign of the shocks around political events, and (Rivolta and Trecroci, 2021), who employ sign restrictions in a model featuring uncertainty proxies and EBP to identify uncertainty shocks in

[5] Ludvigson et al.'s (2019) financial and macroeconomic uncertainty measures are based on the data-rich approach developed by Jurado et al. (2015), which models the common component of the time-varying variance of the forecast error of a large number of financial and macroeconomic series. Financial (macro) uncertainty is estimated as the common component of the time-varying volatility of the prediction errors of 148 financial (134 macroeconomic) series. Details on the estimation of these two factors are reported in Ludvigson et al. (2019).

[6] A previous version of the paper (Caggiano et al., 2020a) employed a different identification strategy dealing with restrictions à la (Ludvigson et al., 2019) based on the realization of "large" uncertainty and (in our application) credit supply shocks. We thank Luca Benati (Associate Editor) for his suggestion to switch to the narrative sign restrictions identification à la (Antolín-Díaz and Rubio-Ramírez, 2019). Reassuringly, the findings documented in the current version of the paper are similar to those in Caggiano et al. (2020a).

the US and their effects on emerging economies. Brianti (2020) separately identifies financial and uncertainty shocks using a novel identification approach that crucially relies on the qualitatively different responses of corporate cash holdings to an uncertainty shock (that pushes firms to increase their cash holdings for precautionary reasons) vs. a first-moment financial shock (that leads firms to reduce cash reserves as they lose access to external finance). A related paper is (Benati, 2019), who is concerned with the role played by shocks to Baker et al.'s (2016) economic policy uncertainty (EPU) in driving the US, Canadian, UK, and Euro area business cycles. He finds that it is crucial to separately identify uncertainty and financial shocks to correctly quantify the real impact of the former ones. He then achieves separate identification of these two shocks by requiring the uncertainty (financial) shock to i) explain as much (little) as possible of the forecast error variance decomposition of EPU, and as little (much) as possible of that of EBP. He finds EPU shocks to have substantial effects on the US unemployment rate. Our contribution adds to all these papers by: i) providing a new set-identification approach to disentangle first and second moment financial shocks; ii) offering a quantification of the finance-uncertainty multiplier. Finally, our analysis hinges upon the use of a combination of sign restrictions, part of which are related to selected historical periods that are meant to be informative when it comes to identifying the business cycle effects of uncertainty shocks. A somewhat related literature exploits selected events (e.g., events characterized by abrupt changes in uncertainty indicators, or the price of a safe asset such as gold) to overcome endogeneity via a proxy-SVAR approach (see, e.g., Carriero et al., 2015, Piffer and Podstawski, 2018, Alessandri et al., 2020). With respect to these contributions, we pursue set-identification (as opposed to point-identification), deal with different measures of uncertainty, control for the response of credit in assessing the business cycle effects of uncertainty shocks, and exploit such response to quantify the finance-uncertainty multiplier.

From a theoretical standpoint, our paper offers support to microfounded DSGE models jointly modeling uncertainty shocks and financial frictions (Gilchrist et al., 2014; Christiano et al., 2014; Bonciani and van Roye, 2016; Arellano et al., 2019; Brand et al., 2019; Alfaro et al., 2019; Chatterjee et al., 2020). In particular, we share with Alfaro et al. (2019) the goal of quantifying the FUM. Alfaro et al. (2019) first provide empirical evidence on the FUM by working with micro-data related to US publicly-listed firms. They find that financial frictions amplify the real impact of uncertainty shocks, with a multiplier as large as 3 during the Great Recession. Then, they build a microfounded framework where firms face a fixed cost of investment, and where raising external funds is costly too. The model is shown to replicate their main empirical facts, with a multiplier as large as 2. Our VAR estimates also point to a FUM of about 2 (median value), i.e., they suggest a drop in output due to an uncertainty shock twice as large in presence of financial frictions than in a frictionless world. Our results, which are fully in line with Alfaro et al.'s (2019), are obtained with a completely different empirical strategy (simulations with a micro-founded DSGE framework calibrated with micro-data in their case, time-series analysis with macro data in ours). Finally, our results are consistent with recent micro-based evidence associating jumps in aggregate uncertainty with banks' decisions of reducing lending to the private sector (Alessandri and Bottero, 2020) and financially constrained firms cutting their investment more than unconstrained firms following an uncertainty shock (Alfaro et al., 2019).

3. Empirical approach

Data and VAR specification. We work with a six-lag structural VAR model estimated on monthly US data, sample: January 1973-February 2020. The beginning of the sample is justified by the availability of the EBP series. The end of the sample is justified by the findings in Lenza and Primiceri (2020), who show that dropping the COVID-19-related observations, which are characterized by an enormous volatility with respect to the rest of the sample, is sensible when it comes to parameter estimation and inference (for a related paper dealing with COVID-19 observations in a multivariate context, see Carriero et al. (2020)).

Formally, the structural VAR we work with reads as follows:

$$\mathbf{y}_t'\mathbf{A}_0 = \sum_{\ell=1}^{p} \mathbf{y}_{t-\ell}'\mathbf{A}_\ell + \mathbf{c} + \varepsilon_t' \tag{1}$$

where $\mathbf{A}_0$ (which is invertible) and $\mathbf{A}_\ell$ are matrices of coefficients, $\mathbf{c}$ is a vector of parameters, ε_t is a vector of structural shocks, p is the number of lags of the VAR, and $1 \le t \le T$, T being the sample size. Conditional on past information and initial conditions $\mathbf{y}_0, \dots, \mathbf{y}_{1-p}$, the vector ε_t is assumed to be Gaussian with zero mean and covariance matrix $\boldsymbol{I}_n$, i.e., an identity matrix of size n, where n is the number of modeled variables.

It is convenient to re-write Eq. (1) as follows:

$$\mathbf{y}_t'\mathbf{A}_0 = \mathbf{x}_t'\mathbf{A}_+ + \varepsilon_t' \tag{2}$$

where $\mathbf{A}_+' = [\mathbf{A}_1', \dots, \mathbf{A}_p', \mathbf{c}']$ and $\mathbf{x}_t' = [\mathbf{y}_{t-1}', \dots, \mathbf{y}_{t-p}', 1]$. The reduced-form representation implied by this equation is:

$$\mathbf{y}_t' = \mathbf{x}_t'\mathbf{B} + \mathbf{u}_t' \tag{3}$$

where $\mathbf{B} = \mathbf{A}_+\mathbf{A}_0^{-1}$, and the reduced-form innovations $\mathbf{u}_t' = \varepsilon_t'\mathbf{A}_0^{-1}$, whose covariance matrix is $E(\mathbf{u}_t\mathbf{u}_t') = \mathbf{\Sigma} = (\mathbf{A}_0\mathbf{A}_0')^{-1}$. The matrices $\mathbf{B}$ and $\mathbf{\Sigma}$ are the reduced-form parameters, while $\mathbf{A}_0$ and $\mathbf{A}_+$ are the structural parameters.

Let $\mathbf{\Theta}= (\mathbf{A}_0, \mathbf{A}_+)$ collect the value of the structural parameters. We can consider alternative parameterizations of the structural VAR (2) defined by $\mathbf{B}$, $\mathbf{\Sigma}$, and $\mathbf{Q}$, where $\mathbf{Q} \in O(n)$, which is the set of $\mathbf{Q}$ matrices such that $\mathbf{QQ}' = \mathbf{Q}'\mathbf{Q} = \boldsymbol{I}_n$. Let $h(\mathbf{\Sigma})$ be a square matrix of dimension n such that $h(\mathbf{\Sigma})'h(\mathbf{\Sigma}) = \mathbf{\Sigma}$. Given a decomposition h (typically, the Cholesky factor of the matrix $\mathbf{\Sigma}$), (Antolín-Díaz and Rubio-Ramírez, 2019) show how to define the mapping between $\mathbf{\Theta}$ and $(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q})$.

Hence, by drawing different realizations of $\mathbf{Q}$ from the set $O(n)$, we can consider different sets of values of the structural parameters $\mathbf{\Theta}$ all consistent with the data (see also Arias et al., 2018). Antolín-Díaz and Rubio-Ramírez (2019) develop a Bayesian approach to draw from the uniform-normal-inverse-Wishart posterior distribution of $(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q})$ conditional on traditional, ratio, and narrative sign restrictions, which is what we do in our exercise. We refer the reader to Antolín-Díaz and Rubio-Ramírez (2019) for details on the theoretical properties of their approach, as well as the algorithm to implement it.

Data. We model the following seven-variable vector of US macroeconomic indicators: $\mathbf{y}_t' = [U_{ft}, EBP_t, U_{mt}, 100\log(RGDP_t), 100\log(PCE_t), SR_t, 100\log(SP500)]'$, where U_{mt} and U_{ft} are, respectively, the macroeconomic and financial uncertainty proxies constructed by Ludvigson et al. (2019); EBP_t is the excess bond premium measure proposed by Gilchrist and Zakrajšek (2012) and regularly updated as explained in Favara et al. (2016); $RGDP_t$ is the real GDP index at monthly frequencies constructed by Stock and Watson (2010) and updated by 'Macroeconomic Advisers';[7] *PCE* is the personal consumption expenditures deflator monitored by the Fed; SR_t is the shadow policy rate estimated by Wu and Xia (2016);[8] *SP*500 is Standard and Poor's 500 stock market index. Among all available proxies of uncertainty, we decided to use Ludvigson et al.'s (2019) uncertainty indices for three reasons. First, they provide different measures for macro and financial uncertainty constructed in a similar way, so that any differences in their behavior cannot be attributed to a different measurement approach. This is important because, as stressed in Ludvigson et al. (2019), the response of macroeconomic uncertainty to financial uncertainty shocks is crucial to correctly quantify the magnitude and the persistence of the real activity contraction triggered by heightened uncertainty. This is why, even though we are not directly interested in identifying macro uncertainty shocks, we include macroeconomic uncertainty in our VAR. Second, they have a forward looking nature, as they capture the uncertainty about current outcomes given the information set available today. Third, they are considered state-of-the-art measures and have become highly popular in the uncertainty literature.[9] Turning to the excess bond premium, (Gilchrist and Zakrajšek, 2012) shows that jumps of this variable -which, as written above, approximate credit supply disruptions - are associated with significant deteriorations of the business cycle. EBP represents the component of the micro-founded "GZ" credit spread constructed by Gilchrist and Zakrajšek (2012) that is purged from the expected default risk of borrowers. Importantly, (Gilchrist and Zakrajšek, 2012) find the predictive ability of the GZ credit spread for future economic activity to be superior to that of Moody's Baa-Aaa corporate bond credit spread and that of the "paper bill" spread, i.e., the spread between the one-month AA-rated non-financial commercial paper yield and the one-month Treasury yield. Crucially for our study, and differently from the latter two spreads, EBP features a negative forecast error (conditional on our estimated VAR) in 1987M10, the month of the Black Monday. As explained below, our assumption is that such a negative realization of the EBP residual in that month is driven by an expansionary credit supply shock due to the Federal Reserve persuading the banking sector to keep lending liquidity to the private sector in spite of the uncertain economic conditions prevailing at the time. We expand on this assumption and explain our identification strategy below.

Identification. As anticipated above, we move from the reduced-form VAR to the structural one by imposing restrictions that retain models that imply impulse responses and contributions of crucial shocks in selected historical periods in line with our a-priori on the business cycle effects of financial and uncertainty shocks. We work with three different types of restrictions, i.e., traditional sign restrictions, which we impose on some impulse responses of our modeled variables to the shocks of interest; ratio restrictions, which we impose on some ratios of impulse responses; and narrative sign restrictions, which we relate to historical events that are informative on the contribution of financial uncertainty and EBP shocks as far as the forecast errors of financial uncertainty and EBP are concerned.

Traditional sign restrictions. We impose traditional sign restrictions on the impulse responses of financial uncertainty, EBP, and macroeconomic uncertainty to a financial uncertainty and EBP shock. In particular, we require our retained models to imply an on-impact positive response of these variables to a positively signed financial uncertainty shock as well as to a positively signed EBP shock. The requirement of a positive response of EBP (financial uncertainty) to a financial uncertainty (EBP) shock is justified by solid evidence on the conditional response of credit stress (financial uncertainty) to a jump in volatility (credit stress) (Caldara et al., 2016; Furlanetto et al., 2019). A positive response of macroeconomic uncertainty to a financial uncertainty and EBP shocks is supported by the finding by Ludvigson et al. (2019) on the endogeneity of macroeconomic uncertainty. We leave the response of other macroeconomic indicators unsigned. Hence, non-zero responses of output, prices, the policy rate, and stock prices to our identified shocks should be read as a genuine empirical finding of our analysis.

Ratio restrictions. To tackle the challenge of separating EBP and financial uncertainty shocks, we follow the approach proposed by Furlanetto et al. (2019) and impose restrictions on the ratios of the impulse responses of financial uncertainty and EBP. In particular, we impose that a financial uncertainty (EBP) shock generate an on-impact response of the finan-

[7] We thank Luca Benati for kindly providing us with this series. The original series constructed by Stock and Watson (2010), and available for the sample 1959M1-2010M12, can be found at http://www.princeton.edu/mwatson/mgdp_gdi.html.

[8] The estimate of the shadow rate is available at Cynthia Wu's webpage, i.e., https://sites.google.com/view/jingcynthiawu/.

[9] Fig. 1 plots the VXO as a measure of financial uncertainty instead of Ludvigson et al.'s (2019) financial uncertainty because of the attention placed by financial market operators, policymakers, and the media on this measure of implied financial volatility. For reasons detailed in the text, we prefer to consider Ludvigson et al.'s (2019) financial uncertainty measure when conducting our analysis. It is worth pointing out that the correlation between Ludvigson et al.'s (2019) financial uncertainty index and the VXO is positive, large (0.83), and significant in our sample. Our Appendix documents the comovement of these two financial volatility series.

cial uncertainty-EBP ratio bigger (smaller) than one.[10] We exploit the same idea to separate financial and macroeconomic uncertainty shocks and impose that a financial (macroeconomic) uncertainty shock generate an on-impact response of the financial uncertainty-macroeconomic uncertainty ratio bigger (smaller) than one.[11]

Narrative sign restrictions. On top of the above described restrictions, we impose restrictions related to the Black Monday and the Great Recession, which are likely to carry relevant information on the real impact of financial uncertainty and EBP shocks. Following Antolín-Díaz and Rubio-Ramírez (2019), we focus on the contribution of financial uncertainty (EBP) shocks to the forecast error of financial uncertainty (EBP), and require that such shocks be the most important drivers of such forecast error in the following dates: 1987M10 (Black Monday) and 2008M9 and 2008M10 (Great Recession). More formally, let $\left|H_{i,j,t,t+h}(\mathbf{\Theta}, \varepsilon_t, \ldots, \varepsilon_{t+h})\right|$ be the absolute value of the contribution of the jth shock to the observed unexpected change in the ith variable between periods t and $t+h$. Then, for each date $t \in \{1987M10, 2008M9, 2008M10\}$, we impose that

$$\left|H_{U_f,\varepsilon^{U_f},t-1,t}\right| - \max_{j' \neq \varepsilon^{U_f}} \left|H_{U_f,j',t-1,t}\right| > 0$$

and

$$\left|H_{EBP,\varepsilon^{EBP},t-1,t}\right| - \max_{j' \neq \varepsilon^{EBP}} \left|H_{EBP,j',t-1,t}\right| > 0$$

Narrative restrictions: Black Monday. We impose that the U_f (EBP) shock be the most relevant driver of U_f (EBP) in October 1987. It is of interest to analyze what happened a few days before the Black Monday to understand what the main driver of U_f and EBP could be and, consequently, our identification strategy. As Bernhardt and Eckblad (2013) point out in their essay on the Black Monday, the first half of 1987 was characterized by a race upward by stock markets. The Dow Jones Industrial Average (DJIA) had gained 44% by late August in a seven-month span. Concerns of an asset bubble started to raise, and uncertainty surrounding the future value of the stock market began to mount. Bad news regarding the economic outlook emerged in mid-October (Carlson, 2007). In particular, the Ways and Means Committee of the US House of Representatives filed legislation to eliminate tax benefits associated with financing mergers. Moreover, the August trade deficit was quantified to be much larger than expected by the Commerce Department. This latter news led to a decline of the US dollar, and expectations about a future monetary policy tightening built up. The consequent rise in interest rates put further downward pressure on equity prices. Traders started to sell, and on October 16, "triple witching" occurred, i.e., monthly expirations of options and futures contracts occurred on that day. As pointed out by Carlson (2007), the expiry of a variety of options made it difficult for investors to roll their positions into new contracts for hedging purposes. Hence, liquidity was invested in future markets, and arbitrageurs traded stocks for futures, which put further downward pressures on financial assets. On Friday October 16, the DJIA lost 4.6 percent. The day after, Treasury Secretary James Baker publicly threatened to de-value the US dollar to improve the trade deficit.[12]

These events were major contributors to the catastrophic Black Monday (October 19). When the US markets opened in the morning, stock markets in and around Asia had already began plunging. Investors quickly moved to liquidate, creating a cascade in stock markets internationally. Information about current market conditions became difficult to obtain, a fraction of the stocks temporarily did not open for trading, and rumors about market closings started spreading around (Carlson, 2007). We interpret this element as a genuine uncertainty shock, which justifies our assumption of such a shock being the most relevant driver of financial uncertainty in October 1987. This uncertainty was pretty costly. Because of it, investors sought to sell and close out their positions. The DJIA crashed at the opening bell, recording a minus 22.6 percent at the end of the day.

The Federal Reserve, at the time led by Alan Greenspan, promptly stepped in. Four things happened. First, on Tuesday morning, the Fed stated its readiness to support market liquidity. Second, the Fed actually followed up its statement and - as Bernanke (1990) puts it - "flooded the system with liquidity" (the federal funds rate was cut by 50 basis points that day).[13] Third, it closely monitored financial markets and enabled extraordinary operations to minimize defaults.[14] Fourth, the Fed successfully persuaded banks to continue lending on their usual terms in spite of the chaotic conditions and the possibility of adverse selection of borrowers (not necessarily a profit-maximizing move). According to Bernanke (1990), the 10 largest New York banks nearly doubled their lending to securities firms during the week of October 19. These interventions paid off, and the US stock market recovered pretty quickly, gaining back 57 percent of the total Black Monday downturn in just two trading sessions.

[10] Caldara et al. (2016) separate first and second moment shocks by appealing to a penalty function identification strategy which relies on the ordering of the two first and second moment proxies in the vector. The advantage of the identification restriction pursued here is that it does not require to assume a recursive economy.

[11] These ratio restrictions are sensible only if the variables involved in the ratios are measured in the same units and have the same scale. To ensure that our variables meet these requirements, we adjusted the EBP and U_m series such that their first two moments are equivalent to the first two moments of the U_f series.

[12] More detailed accounts on the days leading to the Black Monday can be found in Carlson (2007) and Bernanke (1990).

[13] At a monthly level, the effective federal funds rate dropped from 7.29% in October 1987 to 6.69% in November 1987.

[14] For instance, when First Options of Chicago - a large clearing firm - was in danger of defaulting, the Federal Reserve allowed Continental Illinois (First Options of Chicago's parent firm) to inject funds into its subsidiary, a move that drastically reduced the risk of the closing of the options exchange (see Bernanke (1990, p. 148)).

While financial crises before and after the Black Monday have often been associated with issues affecting the banking sector and a drop in real activity, the October 1987 one was not (Kohn, 2006). Hence, the behavior of EBP in that period can be hardly attributed to a business cycle shock, or to a financial volatility shock.[15] Inflation does not seem to have much to do with EBP in this story either. The response of monetary policy was certainly strong and rapid, and likely helped maintaining credit lines to corporate firms in check. However, to the extent that such a response can be read as a systematic response by the Federal Reserve to evolving economic and financial conditions, the behavior of the EBP should not be attributed to a monetary policy shock.[16] Instead, the fact that the Federal Reserve managed to persuade the banking system to keep providing liquidity to firms over what they would have normally done in response to economic conditions represents a negative EBP shock (i.e., a positive credit supply shock) that is likely to be the most relevant driver of EBP in October 1987.[17] This is the reason behind our identification restriction on the EBP shock - which we interpret here as a ”persuasion shock” by the Federal Reserve - as the most relevant driver of EBP in October 1987.

Narrative restrictions: Great Recession. The Great Recession has been scrutinized at length. There is wide agreement on the fact that it was a crisis with financial origins, with a collapse of the credit and, more broadly, financial sector that dramatically accelerated after Lehman Brothers' bankruptcy on September 14, (Gertler and Gilchrist, 2017). The reading of this first-moment negative shock we propose through the lens of our VAR is that of a large and negative EBP shock that, among other things, led to a quick and abrupt increase in EBP. At the same time, a spectacular bout in financial volatility materialized after September 14, with a huge uncertainty surrounding a number of crucial elements of the economic system (from the health and survival of credit and financial intermediaries, to bailout decisions by the Government and the Federal Reserve, to the proximity of the zero lower bound, the effectiveness of unprecedented unconventional monetary policy moves, the size and effectiveness of the fiscal packages put in place by the Obama Administration, and so on) that led to a record-high level of financial volatility. In our VAR, we interpret this unforeseen jump in financial uncertainty in September 2008 as mostly driven by a financial uncertainty shock. To capture the persistence of this jump, we also require the same for the following month, i.e., October 2008. Symmetrically, and in order to not overstate the relative relevance of uncertainty shocks vs. EBP shocks, we require that EBP shock be the most relevant driver of the unforeseen component of EBP in October 2008. Recent contributions on the role played by uncertainty shocks as drivers of the US business cycle classify financial uncertainty as exogenous (Angelini and Fanelli, 2019; Angelini et al., 2019; Ludvigson et al., 2019). Notably, our assumption on the uncertainty shock being the major driver of unexpected realizations of financial uncertainty in 2008M9 and 2008M10 is consistent with - indeed, less restrictive than - the requirement of financial uncertainty being exogenous.

Role of the narrative restrictions in our identification strategy. What is the role played by the imposition of our narrative restrictions in our identification strategy? Our claim is that the imposition of these restrictions on top of traditional sign and ratio restrictions not only sharpens the identification of the shocks of interest (U_f and EBP shocks), but also works in favor of separating these shocks from the other shocks hitting the system. To see this point, let's take for instance the 1987M10 (Black Monday) requirements. When we require the U_f shock to be the most important contributor to the observed unexpected movements of U_f (let's call it requirement # 1), we are separating this shock from all other shocks (EBP shock included), because none of the other shocks will be as important for the financial uncertainty forecast error in 1987M10. The same argument applies when we require the EBP shock to be the most important contributor to the observed unexpected movements of EBP (let's call it requirement #2). By doing so, we are separating this shock from all other shocks (U_f shock included), because none of the other shocks will be equally important for unexpected change in EBP in 1987M10. But notice that our identification strategy jointly imposes requirements #1 and #2. Hence, for an impulse vector to meet both these requirements, it has to be true that: (a) the U_f and EBP shocks are separately identified, and (b) these two shocks are separated from the rest of the shocks hitting the system. The same is true for the other dates we work with (2008M9 and 2008M10). Hence, the separation between the shocks of interest and those that are not of interest verifies.[18]

---

[15] As correctly pointed out by a referee, the Chicago Fed National Financial Conditions index (NFCI) - a broad measure of financial stress - is highly correlated with financial uncertainty (0.48 with the measure of financial uncertainty used in this paper in the sample 1973M1-2020M2 we work with), and both measures display local peaks in October 1987. Hence, such an alternative measure of financial stress does not align well with our narrative. Three things are worth noticing here. First, our choice of EBP is justified by its low realization in correspondence with the Black Monday, which enables us to argue that it was a credit supply shock, as opposed to a financial volatility shock, the main driver behind EBP during that event. Second, unlike other financial stress indicators, EBP captures financial stress that cannot be explained by firms' or markets' fundamentals, and as such represents a proxy closer to the concept of credit market disruptions. Third, we prefer EBP over the NFCI because some of the 34 financial indicators used to construct the latter are volatility indicators (among which, the VIX). Hence, the use the NFCI would make our approach to separate pure financial uncertainty shocks from first-moment shocks problematic. Information on the construction of the NFCI can be found at https://www.chicagofed.org/publications/chicago-fed-letter/2017/386.

[16] For evidence on the systematic response of the Federal Reserve to financial volatility, see Evans et al. (2015) and Caggiano et al. (2018).

[17] Notice that, as stressed by Bernanke (1990), *"[...] making these loans must have been a money-losing strategy from the point of view of the banks (and the Fed); otherwise, Fed persuasion would not have been needed. But lending was a good strategy for the preservation of the system as a whole."* This possible deviation from a profit-maximizing behavior supports our interpretation of the change in EBP in 1987 as a mainly exogenous one.

[18] Another way of explaining this intuition is the following. Suppose we have a three-variate VAR where $\mathbf{y}_t = [U_f, EBP, z]'$ are the modeled variables, and $\varepsilon_t = [\varepsilon^{U_f}, \varepsilon^{EBP}, \varepsilon^{z}]'$ are the structural shocks hitting the system. Our goal is identify the first two shocks, i.e., ε^{U_f} and ε^{EBP}. We impose the following restrictions on the historical decomposition: 1) ε^{U_f} is the most important contributor to the unexpected change in U_f between 1987M09 and 1987M10; 2) ε^{EBP} is the most important contributor to the unexpected change in *EBP* between 1987M09 and 1987M10 (again taken as a reference date to fix ideas - the same reasoning applies when we consider the Great Recession dates). Let $H_{i,j,t}$ be the contribution of the *jth* shock to the unexpected change in the *ith* variable between period $t-1$ and period t. Then the first restrictions jointly imposes that

$$\left|H_{U_f,\varepsilon^{U_f},1987M10}\right| - \left|H_{U_f,\varepsilon^{EBP},1987M10}\right| > 0$$

Table 1
Identification restrictions. Constraints imposed to separately identify financial uncertainty and excess bond premium shocks. Constraints involving ratios of variables: Uf stands for financial uncertainty; EBP for excess bond premium; Um for macro uncertainty. Shocks identified by epsilons. H stands for the contribution of a given shock j to a given variable i between t-1 and t, and it is considered in absolute value. Identified shocks are associated with a positive jump in the corresponding variable (i.e., a positive jump in financial uncertainty, EBP, and macroeconomic uncertainty).

Traditional sign restrictions
$\frac{\partial U_{ft}}{\partial \varepsilon_t^{U_f}} > 0$ $\frac{\partial EBP_t}{\partial \varepsilon_t^{U_f}} > 0$ $\frac{\partial U_{mt}}{\partial \varepsilon_t^{U_f}} > 0$
$\frac{\partial U_{ft}}{\partial \varepsilon_t^{EBP}} > 0$ $\frac{\partial EBP_t}{\partial \varepsilon_t^{EBP}} > 0$ $\frac{\partial U_{mt}}{\partial \varepsilon_t^{EBP}} > 0$
Ratio restrictions
$\frac{\partial EBP_t}{\partial \varepsilon_t^{U_f}} < \frac{\partial U_{ft}}{\partial \varepsilon_t^{U_f}}$ $\frac{\partial EBP_t}{\partial \varepsilon_t^{EBP}} > \frac{\partial U_{ft}}{\partial \varepsilon_t^{EBP}}$
$\frac{\partial U_{ft}}{\partial \varepsilon_t^{U_f}} > \frac{\partial U_{mt}}{\partial \varepsilon_t^{U_f}}$ $\frac{\partial U_{ft}}{\partial \varepsilon_t^{U_m}} < \frac{\partial U_{mt}}{\partial \varepsilon_t^{U_m}}$
Narrative sign restrictions
$\left\lvert H_{U_f,\varepsilon^{U_f},t-1,t} \right\rvert - \max_{j' \neq \varepsilon^{U_f}} \left\lvert H_{U_f,j',t-1,t} \right\rvert > 0$
$\left\lvert H_{EBP,\varepsilon^{EBP},t-1,t} \right\rvert - \max_{j' \neq \varepsilon^{EBP}} \left\lvert H_{EBP,j',t-1,t} \right\rvert > 0$
$t \in \{1987M10, 2008M9, 2008M10\}$

The whole set of identification restrictions we impose in our analysis is collected in Table 1. The joint imposition of the above described constraints delivers a set of 1,517 models meeting all imposed restrictions out of 30,530,000 overall draws.[19] The impact of the narrative sign restrictions is massive, with the number of retained models going up to 35,005 if we drop them. This evidence clearly speaks in favor of the informativeness of our restrictions - in particular, the narrative ones - as far as the separate identification of financial uncertainty and credit supply shocks is concerned.

4. Empirical findings

Impulse responses. Fig. 2 plots the impulse responses to a financial uncertainty shock and to a shock to EBP according to our VAR (size of the shocks: One standard deviation). Following an exogenous jump in financial uncertainty, real GDP temporarily contracts, with a median peak response of -0.2% after one year, before gradually going back to trend after about 2 years and a half (considering the associated 68% credible set). The recessionary effect of uncertainty shocks are line with a vast empirical literature surveyed by Bloom (2014) and Castelnuovo (2019). EBP quickly increases, tops after five months, then gradually goes back to the pre-shock level. While these responses do not necessarily point to the existence of the FUM, they are consistent with it - we elaborate on this point below. Interestingly, our model points to an increase in macroeconomic uncertainty in the short-run. This evidence is consistent with the findings in Ludvigson et al. (2019), who identify financial uncertainty as a driver of the business cycle, and macroeconomic uncertainty as a consequence of movements in output (for related evidence, see Angelini et al. (2019)). The stock market plummets after an uncertainty shock, with a peak realization of -2.7% after five months, and a gradual, persistent return to its pre-shock trend in the following years. The effects of inflation are unclear. This finding can be explained by thinking of the conflicting effects on prices due to an uncertainty shock. On the one hand, following a Phillips curve-logic, the weakening of the business cycle would naturally call for temporary deflation. On the other hand, a jump in uncertainty implies an increase in prices as an optimal response by firms that aim at not getting stuck in unfavorable contracts should a possible future recession not

---

and

$$\left\lvert H_{U_f,\varepsilon^{U_f},1987M10} \right\rvert - \left\lvert H_{U_f,\varepsilon^{z},1987M10} \right\rvert > 0.$$

This restriction is enough to separate ε^{U_f} from both ε^{EBP} and ε^{z} shocks. The second restriction jointly imposes that

$$\left\lvert H_{EBP,\varepsilon^{EBP},1987M10} \right\rvert - \left\lvert H_{EBP,\varepsilon^{U_f},1987M10} \right\rvert > 0$$

and

$$\left\lvert H_{EBP,\varepsilon^{EBP},1987M10} \right\rvert - \left\lvert H_{EBP,\varepsilon^{z},1987M10} \right\rvert > 0$$

so that ε^{EBP} is separated from ε^{z}. Hence: (a) the financial and credit supply shocks are separately identified; (b) these shocks are separately identified from the ε^{z} shock. This reasoning straightforwardly extends to the case of z being a vector.

[19] We see the fact that our identifying constraints select 1517 models out of more than 30 millions as a good sign. This is in line with Uhlig's (2017) Principle 7: *"When a lot of draws are rejected, the identification is sharp. Good!"*. In other words, the large number of discarded models should be interpreted as pointing at the informativeness of our imposed identifying restrictions, more than at an issue affecting our structural VAR.

Table 2
Role of financial uncertainty and EBP shocks: Forecast error variance decomposition. FEVD computed by considering a 2-year horizon. RGDP, PCE, and SP500 in logs and multiplied by 100.

Shock/Variable	U_f	EBP	U_m	RGDP	PCE	SR	SP500
U_f shock	0.29 [0.14,0.52]	0.15 [0.08,0.23]	0.14 [0.05,0.30]	0.16 [0.05,0.38]	0.06 [0.01,0.17]	0.08 [0.03,0.26]	0.33 [0.14,0.56]
EBP shock	0.07 [0.02,0,18]	0.31 [0.19,0.44]	0.12 [0.05,0.25]	0.17 [0.04,0.41]	0.09 [0.02,0.33]	0.12 [0.04,0.33]	0.17 [0.04,0.39]

materialize (Born and Pfeifer, 2014; Fernández-Villaverde et al., 2015; Born and Pfeifer, 2020). Overall, these two conflicting effects could very well cancel each other out when it comes to the response of inflation to an uncertainty shock. Finally, the policy rate gradually decreases, peaks at -0.14%, then goes back to its pre-shock trend. This response is consistent with a standard policy response to recessionary shocks, as well as - possibly - to the stock market fall (Furlanetto, 2011).

Turning to the EBP shock (size: one standard deviation), our impulse responses suggest a recessionary effect similar to the one triggered by a financial uncertainty shock. This result confirms the findings in Gilchrist and Zakrajšek (2012) and Barnichon et al. (2020), who run VAR exercises that do not feature any measure of uncertainty. Both financial and macroeconomic uncertainty temporarily increase after the shock, before going back to their pre-shock level. This last result, coupled with the one on the response of EBP to an uncertainty shock, corroborates our choice of using an identification scheme alternative to the Cholesky decomposition of the covariance matrix of the estimated residuals to identify financial uncertainty shocks when measure of financial stress belong to the VAR. The stock market negatively reacts to the simulated disruption in credit supply, peaks at -1.8% after five months, and gradually goes back to the trend. Monetary policy responds to this shock too. As in the case of the financial uncertainty shock, this response is consistent with a central bank responding the recessionary shocks and - again, possibly - a stock market drop. As before, the response of inflation is unclear. Again, conflicting forces may very well be at work in this case too, with the usual deflationary pressures related to a weakening of the business cycle contrasted by the inflationary pressures due to the augmented borrowing costs - here proxied by EBP- faced by firms that need to externally finance their productive activities (Del Negro and Schorfheide, 2012; Abbate et al., 2016), or due to the need of firms to raise their liquidity after a negative financial shock (Brianti, 2020).

Forecast error variance decomposition. How relevant are financial uncertainty and EBP shocks? Table 2 collects the outcome of the forecast error variance decomposition analysis conducted by considering a 2-year ahead horizon. The two shocks combined explain about 33% of the volatility of output, with a contribution of financial uncertainty shocks only equal to 16%. Differently, the impact of these two shocks on inflation is found to be more moderate, with financial uncertainty shocks explaining just 6% of its volatility, and EBP shocks 9%. The impact on the policy rate is non-negligible, with uncertainty accounting for 8% of the volatility of the shadow rate, and EBP shocks 12%. The impact of uncertainty shocks on credit and financial indicators is 15% in the case of EBP and 33% as far as the stock market is concerned, i.e., almost twice as large as that of EBP shocks. Finally, both shocks (combined) affect about 1/4 of the volatility of macroeconomic uncertainty. These results, obtained with a novel identification strategy that separates first and second moment financial shocks, confirm that financial uncertainty shocks are drivers of the business cycle (Bloom, 2009; Caggiano et al., 2014; Leduc and Liu, 2016; Caldara et al., 2016; Basu and Bundick, 2017; Ludvigson et al., 2019; Angelini and Fanelli, 2019; Angelini et al., 2019), and document an impact of uncertainty shocks comparable with that of first-moment credit supply shocks.

Great Recession: Historical decomposition. It is of interest to quantify the contribution of financial uncertainty and EBP shocks to the output loss recorded during the Great Recession. We focus on the 2007M12-2009M6 period, which is the Great Recession period according to the classification by the National Bureau of Economic Research. Fig. 3 plots the outcome of the historical decomposition analysis that focuses on our two identified shocks. Evidently, the evolution of the total unexpected change in real GDP is closely tracked by the one driven by financial uncertainty shocks as well as EBP shocks. In particular, these two shocks are able to track the acceleration of the decline in output due to Lehman Brothers' bankruptcy and the disruption of the credit and financial markets. At the end of the recession, the two shocks combined account for about 70% of the overall output loss, with a contribution by financial uncertainty shocks of about 24%, and that of EBP shocks of 42%. These contributions, that are larger than the average ones over the business cycle identified by our forecast error variance decomposition analysis, may be explained by the high degree of risk aversion experienced by agents in the economic system during extreme events such as the Great Recession. Bretscher et al. (2018) show that a nonlinear DSGE framework calibrated to match the fall in real activity requires a large degree of households' risk aversion for uncertainty shocks to replicate the facts. Pellegrino et al. (2020) estimate a nonlinear DSGE framework to match the same facts, and also find that a large degree of risk aversion is crucial to generate a slump in output - due to an uncertainty shock - comparable to the historical one. Our findings also corroborate previous analysis (that do not rely on narrative restrictions à la Antolín-Díaz and Rubio-Ramírez (2019) and are not concerned with the finance uncertainty multiplier) that point to uncertainty (Bloom, 2014; Basu and Bundick, 2017; Caggiano et al., 2017; 2020b) and EBP shocks (Barnichon et al., 2020) as major drivers of the Great Recession.

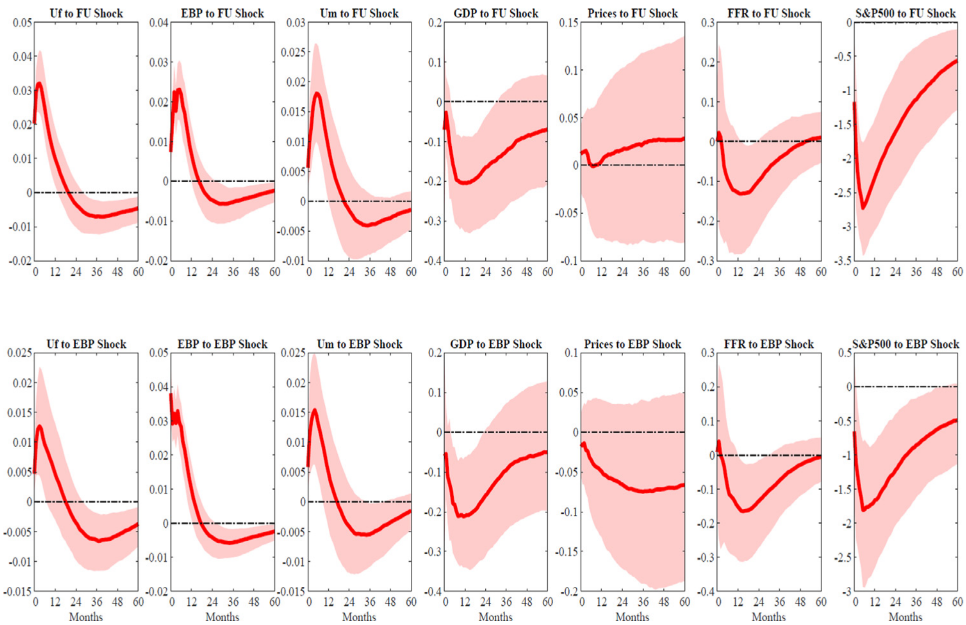

Fig. 2. Impulse responses to identified financial uncertainty and excess bond premium shocks. Top (bottom) row: Responses to a financial uncertainty (excess bond premium) shock. Size of the shocks: One standard deviation. Identification achieved via the mix of event, correlation, sign, and ratio restrictions explained in the text.

5. Finance-uncertainty multiplier

Output. Is the contribution of frictions on the credit market relevant for the transmission of uncertainty shocks? Are the real effects of a jump in uncertainty magnified by the presence of credit frictions, i.e., is there a finance-uncertainty multiplier (FUM), and if so, how large is it? We address these questions by running a counterfactual analysis with our estimated VAR. Such a counterfactual analysis simulates the response of our endogenous variables to an uncertainty shock (size: one standard deviation) while keeping EBP at its pre-shock level. We do so by generating fictitious shocks to EBP that perfectly offset the impact of the financial uncertainty shock on EBP as well as the dynamic feedback effects going from the other endogenous variables of the system to EBP. A milder response of real GDP to an uncertainty shock in this counterfactual scenario would speak in favor of the existence of a FUM.

Fig. 4 contrasts the factual response of real GDP to an uncertainty shock to the one obtained by engineering the just described counterfactual investigation. The figure clearly points to the existence of a FUM, with real GDP in the counterfactual scenario dropping much less (peak response: -0.08% vs. -0.20% in the factual analysis) and clearly remaining much closer to its pre-shock trend within the horizon of interest (2 years, i.e., a horizon according to which the 68% credible set surrounding the median response of real GDP in the factual analysis still does not include the zero value - see Fig. 2). Then, per each retained model, we quantify the size of the FUM by considering the cumulative responses of real GDP at a two-year horizon. Formally, the cumulative FUM is computed as:

$$FUM(sum) = \frac{\sum_{h=0}^{24}\left[\frac{\partial 100\log(RGDP_{t+h})}{\partial e_t^{Uf}}\right]}{\sum_{h=0}^{24}\left[\frac{\partial 100\log(RGDP_{t+h})}{\partial e_t^{Uf}}\,\middle|\,\frac{\partial EBP_{t+h}}{\partial e_t^{Uf}}=0\right]}$$

where the numerator is the sum of the values of the impulse response of real GDP to an uncertainty shock when the response of EBP is unconstrained, and the denominator is the sum of such values when the response of EBP is kept fixed. This way of computing multipliers naturally accounts for the overall real impact of an uncertainty shock in the two scenarios. However, for realizations of output that cross the zero line over the considered horizon, this way of computing the multiplier may generate an excessive dispersion of realizations of the FUM (when the sum of the values of the counterfactual response of output over the considered horizon gets close to zero).[20] This is the reason why we check the solidity of our

[20] A similar issue typically arises in the fiscal policy literature when it comes to computing the cumulative tax multiplier, which is a function of the ratio between the sum of the values of the response of output to a (say) tax cut and the sum of the reponse of taxes to such a cut. Given that the latter response is endogenous and related to the business cycle, the VAR literature has often documented that an expansionary tax cut can lead to an increase in Government revenues, with the path of taxes quickly switching from negative to positive. Hence, the sum of the response of tax revenues is, for certain

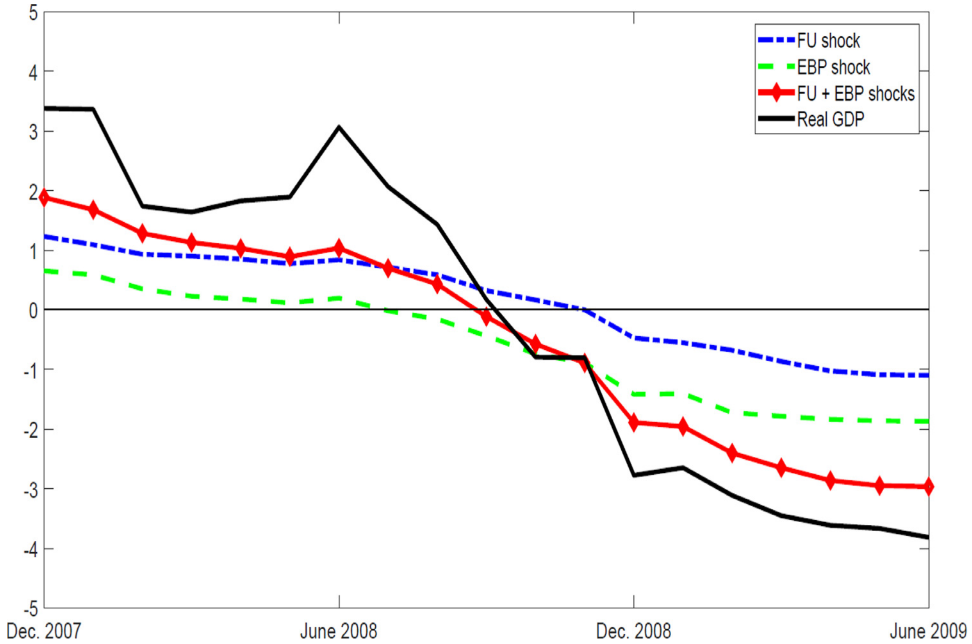

Fig. 3. Historical decomposition of real GDP during the great recession. Sample: 2007M12-2009M6. Observed unexpected change in real GDP attributed to each of the identified shocks (financial uncertainty, EBP shock).

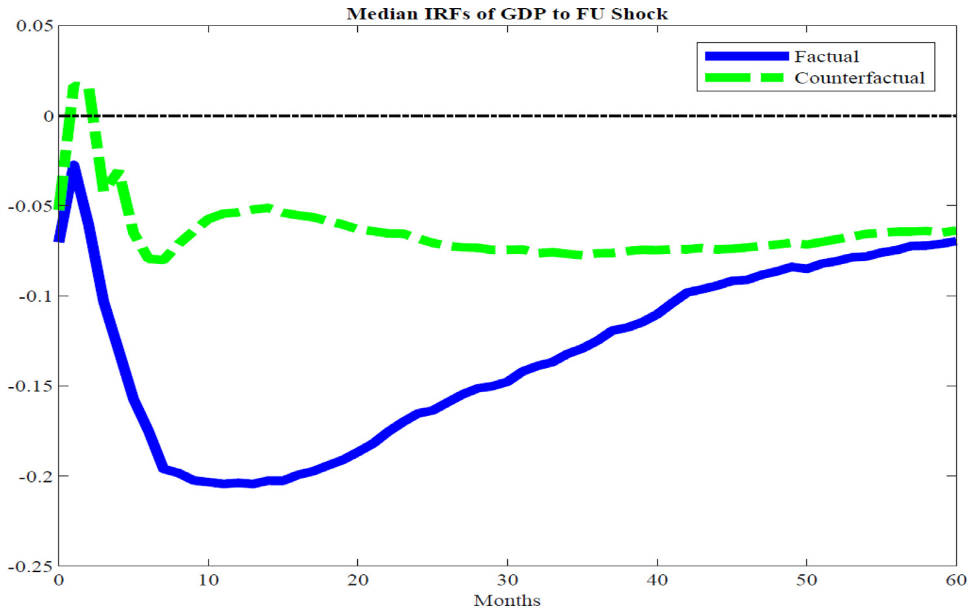

Fig. 4. Response of real GDP to a financial uncertainty shock: Role of EBP. Factual response of real GDP to a financial uncertainty shock as in Fig. 2, i.e., EBP endogenous. Counterfactual response of real GDP to a financial uncertainty shock conditional on a muted response of EBP to such a shock plus feedback effect due to fictitious shocks perfectly offsetting the direct and indirect impact of the uncertainty shock on EBP.

results by also computing the peak FUM as follows:

$$FUM(peak) = \frac{\min\left[\frac{\partial 100\log(RGDP_{t+h})}{\partial e_t^{Uf}}\right]}{\min\left[\frac{\partial 100\log(RGDP_{t+h})}{\partial e_t^{Uf}}\middle| \frac{\partial EBP_{t+h}}{\partial e_t^{Uf}}=0\right]}, h \in [0, 24]$$

horizons, close to zero, and can easily swich sign (from negative to positive), leading to either extremely large positive tax multipliers or extremely large negative ones (see Ramey, 2019). The computation of the peak multiplier is not affected by this issue.

Table 3
Finance Uncertainty Multiplier Estimates. FUM (sum) computed on the basis of the cumulative IRFs of output (factual and counterfactual) over a 2-year horizon. FUM (peak) computed by considering the minima of the factual and counterfactual IRFs of output. Brackets report the 16th and 84th percentiles of the FUM distributions.

Scenario	FUM (sum)	FUM (peak)
Real GDP (baseline)	2.39 [0.30,6.96]	2.23 [1.10,4.12]
Industrial production	2.52 [0.30,6.23]	2.32 [1.14,4.03]
Employment	1.40 [0.38,3.21]	1.59 [0.82,3.17]

where the numerator is the minimum value (i.e., the largest negative realization) of real GDP to an uncertainty shock when the response of EBP is unconstrained, the denominator is the minimum value of such response when the response of EBP is kept fixed.[21]

Table 3 reports the two estimates of the FUM multiplier. Reassuringly, the median values are close to each other, and point to a value of about 2.2-2.4, i.e., credit frictions roughly double the real effects of uncertainty shock. this finding - obtained with a VAR analysis based on aggregate time series - provides an indication qualitatively and quantitatively in line with that of Alfaro et al. (2019), who work with a calibrated micro-founded DSGE framework featuring real option effects and financial frictions and also find a FUM equal to 2.

Alternative real activity indicators. We verify the solidity of our results as well as extend our analysis to the labor market by working with two alternative real activity indicators. The first one is industrial production. In spite of being affected by measurement error (Miron and Zeldes, 1989), this indicator is very popular in applied work with monthly data because its measurement does not rely on interpolation strategies. Moreover, working with a state-of-the-art factor model and a mixed-frequency dataset comprising a large number of US real activity indicators, Andreou et al. (2019) find that a single common factor explains 89% of IP output growth and 61% of total GDP growth despite the diminishing role of manufacturing. The second real activity indicator alternative to real GDP we work with is employment. It is well known that output and the labor market, while being clearly interconnected, do not necessarily go hand-in-hand. A clear example is the aftermath of the Great Recession, which was characterized by a jobless recovery (see, e.g., Coibion et al., 2013, Benati and Lubik, 2014). Hence, it is of interest to check if the finance uncertainty multiplier is not only present and relevant for understanding the response of real GDP to an uncertainty shock, but also for understanding the one of the labor market. One indicator that is often monitored by policymakers is employment.[22] We then re-run our exercise by replacing real GDP with industrial production and employment (one at a time).[23] Table 3 collects the estimates of the sum and peak multipliers (for the sake of brevity, we document the impulse response analysis in our Appendix). Reassuringly, the figures produced with the model with industrial production are very similar to those of the baseline case. As far as employment is concerned, the estimated multipliers point to values close to 1.5. This last piece of evidence: i) points to the existence of a finance uncertainty multiplier also as far as the labor market is concerned; ii) suggests that such a multiplier, while being sizeable, could be lower than the output related one, perhaps due to labor market frictions affecting employment in response to an uncertainty shocks even in absence of credit frictions (see, e.g., Leduc and Liu, 2016, Cacciatore and Ravenna, 2020).

6. Conclusions

This paper documents the presence of a finance uncertainty multiplier (which is, an amplification of the real effects of uncertainty shocks due to financial frictions) for the US economy. We do so by conducting a VAR analysis and appealing to a novel combination of sign, ratio, and narrative restrictions to separately identify financial uncertainty and credit supply shocks. Our estimates suggest that credit frictions may double the response of real activity to an uncertainty shock. The combination of direct real effects of uncertainty shocks and indirect effects due to the presence of the finance uncertainty multiplier implies a 16% contribution of uncertainty shocks to the real GDP business cycle fluctuations. The joint contribution

[21] Purposely, the minimum realizations of the response of industrial production at the numerator vs. denominator in the *FUM* expression need not realize at the very same horizon *h*. This because there is no theoretical reason to believe that the two minimum values should materialize after an equal number of periods. This is exactly one of the points made by Alfaro et al. (2019), i.e., financial frictions affect the shape and persistence via which output responds to an uncertainty shock.

[22] For instance, Romer (2009) - in her account on the collaboration with President Obama aimed at designing a fiscal stimulus to tackle the deterioration of the US labor market - writes: *"The President gave a very concrete metric: he wanted a program that would raise employment relative to what it would be in the absence of stimulus by 3 to 4 million by the end of 2010."*

[23] We keep the same restrictions as in our baseline exercise. Industrial production and employment and unemployment are modeled in logs and multiplied by 100. Both series are available at the Federal Reserve Bank of St Louis' website, with the codes INDPRO (industrial production) and PAYEMS (employment).

of financial uncertainty and credit supply shocks is found to be particularly large during the Great Recession, with about 70% of the drop in output recorded in June 2009 being attributable to these two shocks. An alternative version of our VAR focusing on employment points to a multiplier of about 1.5, therefore suggesting that also the deterioration of the US labor market due to uncertainty shocks is importantly influenced by credit frictions. Our results offer support to the rapid and massive liquidity interventions engineered by the Federal Reserve to avoid the disruption of the credit markets in the United States after the advent of the pandemic.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.euroecorev.2021.103750

References

Abbate, A., Eickmeier, S., Prieto, E., 2016. Financial shocks and inflation dynamicsCAMA Working Paper 53/2016.
Alessandri, P., Bottero, M., 2020. Bank lending in uncertain times. Eur Econ Rev. forthcoming
Alessandri, P., Gazzani, A., Vicondoa, A., 2020. Uncertainty matters: evidence from a high-frequency identification strategyBank of Italy Working Paper No. 1284.
Alessandri, P., Mumtaz, H., 2019. Financial regimes and uncertainty shocks. J Monet Econ 101, 31–46.
Alfaro, I., Bloom, N., Lin, X., 2019. The finance uncertainty multiplieravailable at https://nbloom.people.stanford.edu/research.
Andreou, E., Gagliardini, P., Ghysels, E., Rubin, M., 2019. Inference in group factor models with an application to mixed frequency data. Econometrica 87 (4), 1267–1305.
Angelini, G., Bacchiocchi, E., Caggiano, G., Fanelli, L., 2019. Uncertainty across volatility regimes. Journal of Applied Econometrics 34 (3), 437–455.
Angelini, G., Fanelli, L., 2019. Exogenous uncertainty and the identification of structural vector autoregressions with external instruments. Journal of Applied Econometrics 34 (6), 951–971.
Antolín-Díaz, J., Rubio-Ramírez, J.F., 2019. Narrative sign restrictions. American Economic Review. forthcoming
Arellano, C., Bai, Y., Kehoe, P.J., 2019. Financial markets and fluctuation in volatility. Journal of Political Economy. forthcoming
Arias, J.E., Rubio-Ramírez, J.F., Waggoner, D.F., 2018. Inference based on SVARs identified with sign and zero restrictions: theory and applications. Econometrica 86 (2), 685–720.
Baker, S., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. Quarterly Journal of Economics 131 (4), 1539–1636.
Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., Viratyosin, T., 2020. The unprecedented stock market reaction to covid-19available at https://nbloom.people.stanford.edu/research.
Barnichon, R., Matthes, C., Ziegenbein, A., 2020. Are the effects of financial market disruptions big or small? Review of Economics and Statistics. forthcoming
Basu, S., Bundick, B., 2017. Uncertainty shocks in a model of effective demand. Econometrica 85 (3), 937–958.
Benati, L., 2019. Economic policy uncertainty, the great recession, and the great depressionUniversity of Bern, mimeo.
Benati, L., Lubik, T.A., 2014. The time-varying beveridge curve. In: Advances in Non-Linear Economic Modeling: Theory and Applications, 17, pp. 167–204.
Bernanke, B.S., 1990. Clearing and settlement during the crash. Review of Financial Studies 3 (1), 133–151.
Bernhardt, D., Eckblad, M., 2013. Stock market crash of 1987Federal Reserve Bank of Chicago, available at https://www.federalreservehistory.org/essays/stock-market-crash-of-1987.
Bloom, N., 2009. The impact of uncertainty shocks. Econometrica 77 (3), 623–685.
Bloom, N., 2014. Fluctuations in uncertainty. Journal of Economic Perspectives 28 (2), 153–176.
Bonciani, D., van Roye, B., 2016. Uncertainty shocks, banking frictions, and economic activity 73, 200–219.
Born, B., Pfeifer, J., 2014. Policy risk and the business cycle. J Monet Econ 68, 68–85.
Born, B., Pfeifer, J., 2020. Uncertainty-driven business cycles: assessing the markup channel. Quant Econom. forthcoming
Brand, T., Isoré, M., Tripier, F., 2019. Uncertainty shocks and firm creation: search and monitoring in the credit market. Journal of Economic Dynamics and Control 99, 19–53.
Bretscher, L., Hsu, A., Tamoni, A., 2018. Risk aversion and the response of the macroeconomy to uncertainty shocks. London Business School, Georgia University of Technology, and London School of Economics, mimeo.
Brianti, M., 2020. Financial shocks, uncertainty shocks, and monetary policy trade-offsavailable at https://sites.google.com/site/marcobriantieconomics/.
Cacciatore, M., Ravenna, F., 2020. Uncertainty, wages, and the business cycle. Economic Journal. forthcoming
Caggiano, G., Castelnuovo, E., Delrio, S., Kima, R., 2020a. Financial uncertainty and real activity: The good, the bad, and the uglyCAMA Working Paper No. 67.
Caggiano, G., Castelnuovo, E., Groshenny, N., 2014. Uncertainty shocks and unemployment dynamics: an analysis of post-wwii u.s. recessions. J Monet Econ 67, 78–92.
Caggiano, G., Castelnuovo, E., Nodari, G., 2018. Risk management-driven policy rate gap. Econ Lett 171, 235–238.
Caggiano, G., Castelnuovo, E., Pellegrino, G., 2017. Estimating the real effects of uncertainty shocks at the zero lower bound. Eur Econ Rev 100, 257–272.
Caggiano, G., Castelnuovo, E., Pellegrino, G., 2020. Uncertainty shocks and the great recession: nonlinearities matter. Econ Lett. forthcoming
Caldara, D., Fuentes-Albero, C., Gilchrist, S., Zakrajšek, E., 2016. The macroeconomic impact of financial and uncertainty shocks. Eur Econ Rev 88, 185–207.
Canova, F., de Nicoló, G., 2002. Monetary disturbances matter for business fluctuations in the g-7. J Monet Econ 49, 1131–1159.
Carlson, M., 2007. A brief history of the 1987 stock market crash with a discussion of the federal reserve responseFederal Reserve Board, Finance and Economics Discussion Series No. 2007-13.
Carriero, A., Clark, T. E., Marcellino, M., Mertens, E., 2020. Measuring uncertainty and its effects in the covid-19 eraQueen Mary - University of London, Federal Reserve Bank of Cleveland, Bocconi University, and Deutsche Bundesbank, mimeo.
Carriero, A., Mumtaz, H., Theodoridis, K., Theophilopoulou, A., 2015. The impact of uncertainty shocks under measurement error: a proxy svar approach. Journal of Money, Credit and Banking 47 (6), 1223–1238.
Castelnuovo, E., 2019. Domestic and global uncertainty: A brief survey and some new resultsCESifo Working Paper No. 7900.
Chatterjee, P., Gunawan, D., Kohn, R., 2020. The interaction between credit constraints and uncertainty shocksUniversity of New South Wales and University of Wollongong, mimeo.
Christiano, L., Motto, R., Rostagno, M., 2014. Risk shocks. American Economic Review 104 (1), 27–65.
Coibion, O., Gorodnichenko, Y., Koustas, D., 2013. Amerisclerosis? the puzzle of rising u.s. unemployment persistence. Brookings Pap Econ Act Fall, 193–241.
Del Negro, M., Schorfheide, F., 2012. Dsge model-based forecasting. In: Elliott, G., Timmerman, A. (Eds.), Handbook of Economic Forecasting, 2. Handbooks in Economics, Elsevier, North-Holland.
Evans, C., Fisher, J.D.M., Gourio, F., Krane, S., 2015. Risk management for monetary policy near the zero lower bound. Brookings Pap Econ Act Spring, 141–196.
Faust, J., 1998. The robustness of identified var conclusions about money. Carnegie Rochester Conference Series on Public Policy 49, 207–244.

Favara, G., Gilchrist, S., Lewis, K. F., Zakrajšek, E., 2016. Updating the recession risk and the excess bond premiumFEDS Notes. Washington: Board of Governors of the Federal Reserve System.
Fernández-Villaverde, J., Guerrón-Quintana, P., Kuester, K., Rubio-Ramírez, J.F., 2015. Fiscal volatility shocks and economic activity. American Economic Review 105 (11), 3352–3384.
Furlanetto, F., 2011. Does monetary policy react to asset prices? some international evidence. International Journal of Central Banking 7 (3), 91–111.
Furlanetto, F., Ravazzolo, F., Sarferaz, S., 2019. Identification of financial factors in economic fluctuations. Economic Journal 129, 311–337.
Gertler, M., Gilchrist, S., 2017. What happened: financial factors in the great recession. Journal of Economic Perspectives. forthcoming
Gilchrist, S., Sim, J. W., Zakrajšek, E., 2014. Uncertainty, financial frictions, and investment dynamicsBoston University and Federal Reserve Board of Governors, mimeo.
Gilchrist, S., Zakrajšek, E., 2012. Credit spreads and business cycle fluctuations. American Economic Review 102 (4), 1692–1720.
Jurado, K., Ludvigson, S.C., Ng, S., 2015. Measuring uncertainty. American Economic Review 105 (3), 1177–1216.
Kohn, D.L., 2006. The evolving nature of the financial system - financial crises and the role of the central bank. In: Remarks at the Conference on New Directions for Understanding Systemic Risk, New York, May 18.
Leduc, S., Liu, Z., 2016. Uncertainty shocks are aggregate demand shocks. J Monet Econ 82, 20–35.
Lenza, M., Primiceri, G. E., 2020. How to estimate a var after march 2020available at https://faculty.wcas.northwestern.edu/%7Egep575/research.html.
Lhuissier, S., Tripier, F., 2016. Do uncertainty shocks always matter for business cycles?CEPII Working Paper No. No 2016-19.
Ludvigson, S.C., Ma, S., Ng, S., 2019. Uncertainty and business cycles: exogenous impulse or endogenous response? American Economic Journal: Macroeconomics. forthcoming
Miron, J.A., Zeldes, S.P., 1989. Production, sales, and the change in inventories: an identity that doesn't add up. J Monet Econ 24, 31–51.
Peersman, G., 2005. What caused the early millennium slowdown? evidence based on vector autoregressions. Journal of Applied Econometrics 20, 185–207.
Pellegrino, G., Castelnuovo, E., Caggiano, G., 2020. Uncertainty and monetary policy during the great recessionmimeo, available at https://sites.google.com/site/efremcastelnuovo/home.
Piffer, M., Podstawski, M., 2018. Identifying uncertainty shocks using the price of gold. Economic Journal 128 (616), 3266–3284.
Popp, A., Zhang, F., 2016. The macroeconomic effects of uncertainty shocks: the role of the financial channel. Journal of Economic Dynamics & Control 69, 319–349.
Ramey, V.A., 2019. Ten years after the financial crisis: what have we learned from the renaissance in fiscal research? Journal of Economic Perpectives 33 (2), 89–114.
Redl, C., 2020. Uncertainty matters: evidence from close elections. J Int Econ 124 (103296).
Rivolta, G., Trecroci, C., 2021. Measuring the effects of u.s. uncertainty and monetary conditions on eme's macroeconomic dynamicsUniversità Cattolica del Sacro Cuore - Milan and University of Brescia, mimeo.
Romer, C. D., 2009. The case for fiscal stimulus: the likely effects of the american recovery and reinvestment actSpeech at the Chicago Booth forum, University of Chicago.
Stock, J. H., Watson, M. W., 2010. Research memorandumavailable at http://www.princeton.edu/~mwatson/mgdp_gdi.html.
Stock, J.H., Watson, M.W., 2012. Disentangling the channels of the 2007–2009 recession. Brookings Pap Econ Act Spring, 81–135.
Uhlig, H., 2005. What are the effects of monetary policy? results from an agnostic identification procedure. J Monet Econ 52, 381–419.
Uhlig, H., 2017. Shocks, sign restrictions, and identification. In: Bo, Honoré, Ariel, Pakes, Monika, Piazzesi, Larry, Samuelson (Eds.), Advances in Economics and Econometrics, Vol. 1 and 2: Eleventh World Congress, Chapter 4. Cambridge University Press, Cambridge.
Wu, J.C., Xia, F.D., 2016. Measuring the macroeconomic impact of monetary policy at the zero lower bound. J Money Credit Bank 48 (2–3), 253–291.