A Positive Effect of Uncertainty Shocks on the Economy: Is the Chase Over ?

Nicolas Himounet
Francisco Serranito
Julien Vauday

2022-26 Document de Travail/ Working Paper

EconomiX - UMR 7235 Bâtiment Maurice Allais
Université Paris Nanterre 200, Avenue de la République
92001 Nanterre Cedex

Site Web : economix.fr
Contact : secreteriat@economix.fr
Twitter : @EconomixU

A Positive Effect of Uncertainty Shocks on the Economy: Is the Chase Over ?

Nicolas HIMOUNET[*], Francisco SERRANITO[†] and Julien VAUDAY[‡]

October 2022

Abstract

How large and persistent are the effects of uncertainty shocks on the economy? Are the effects of macroeconomic uncertainty shocks different from those of financial uncertainty shocks? In the empirical literature there was a consensus on an estimated negative impact of uncertainty on macroeconomic variables. Recently, some studies identifying shocks with a novel methodology, namely the events constraint approach, find that macroeconomic uncertainty shocks may trigger an increase in the industrial production. The goal of this paper is to question this striking result. We have identified two main shortcomings in this literature that could explain the positive correlation between macroeconomic uncertainty and economic activity. We show that this method of identification can be sensitive depending on how to identify and select the structural uncertainty shocks in a SVAR model. Our main conclusion is that the controversial result of a positive effect of macroeconomic uncertainty on economic activity does not yet seem to be proven. Whether financial or macroeconomic, there is no evidence allowing for rejection of the hypothesis that they have a negative impact on economic activity.

Keywords: Uncertainty, SVAR, Narrative Sign Restrictions, Economic Activity
JEL Codes: C32, D80, E32

[*]University of Sorbonne Paris Nord, CEPN-CNRS, nicolas.himounet@univ-paris13.fr
[†]University of Paris Nanterre, EconomiX-CNRS, francisco.serranito@parisnanterre.fr
[‡]University of Sorbonne Paris Nord, CEPN-CNRS, julien.vauday@univ-paris13.fr

1 Introduction

What is an uncertainty shock? How large and persistent are the effects of uncertainty shocks on the economy? And, finally, are the effects of macroeconomic uncertainty shocks different from those of financial uncertainty shocks? This paper will address these questions which became fundamental in the economic debate on the growth path after a financial crisis. Indeed, uncertainty could be one of the main causes of the weak recovery following the 2007-2008 financial crisis (Blanchard, 2009; Stock & Watson, 2012; Bloom *et al.*, 2013).

Since the seminal paper of Bloom (2009), a booming economic research has emerged on measuring the effects of uncertainty shocks on economic activity. A wide range of proxies measuring uncertainty has been proposed. Recent contributions include measures based on volatility of stock markets (See, among many others, Bloom, 2009; Gilchrist *et al.*, 2014; Caldara *et al.*, 2016), measures based on the dispersion on expectations about the future economic conditions (See, among many others, Bloom, 2009; Bachmann *et al.*, 2013; Leduc & Liu, 2016), measures based on recent textual analysis techniques of newspapers (See, among many others, Baker *et al.*, 2016; Davis, 2016; Caldara & Iacoviello, 2018). Other studies try to decompose uncertainty between macroeconomic and financial uncertainty applying econometric methodologies (Jurado *et al.*, 2015; Ludvigson *et al.*, 2021).[1] A last branch of empirical studies developed composite indexes combining the measures of the previous categories to summarize the different information (Haddow *et al.*, 2013; Charles *et al.*, 2018) - see Himounet (2022) for an overview.

Structural VAR (SVAR) models have been mostly applied in the empirical literature to identify and investigate the impact of uncertainty shocks on macroeconomic variables (See, among many others, Bloom, 2009; Jurado *et al.*, 2015; Baker *et al.*, 2016; Leduc & Liu, 2016). If any, most research finds a negative effect of uncertainty: a decline in industrial production and a rise

[1]As already stated, the modern approach to assessing uncertainty is based on either a measure of financial market volatility or a measure of "news " that counts the frequency by which some keywords appear in the press. Recently, Manasse *et al.* (2020) proposed an original framework to assess political uncertainty. Using the Brexit event as a natural experiment, they demonstrate that the probability of the outcome of the Referendum derived from the bookmakers' odds can be a good proxy of the political risk in the pound foreign exchange market. This is because, in the case of the UK, the Brexit Referendum has been preceded by an exceptionally liquid online betting market.

in unemployment. These previous findings are consistent with a theoretical literature arguing that uncertainty can have an influence on agents' behaviour (Dixit, 1989; Blanchard, 2009). Uncertainty can lead firms to delay investment and hiring decisions (Bernanke, 1983; Pindyck, 1991) and it can lead consumers to rise their savings for precautionary reasons (Leland, 1968).

Recently, the empirical consensus on the negative impact of uncertainty has been broken by the studies of Ludvigson *et al.* (2021) and Larsen (2021) who demonstrate that uncertainty shocks may trigger an increase in industrial production. More specifically, among all uncertainty shocks, only the macroeconomic ones will have a positive effect on the economy. This striking result is explained by the implementation of a new econometric framework to identify uncertainty shocks in a SVAR model, namely the *event constraints* methodology developed by Ludvigson *et al.* (2021). Applying a similar despite somehow different methodology based on the *narrative sign restrictions* of Antolín-Díaz & Rubio-Ramírez (2018), Larsen (2021) finds also a positive effect of macroeconomic uncertainty on Norway's economic activity. The explanation about the positive effect of uncertainty would be related to *growth options* theories (Segal *et al.*, 2015). The recent technology of Artificial Intelligence (AI) might be a good illustration of such a theory. Indeed, predicting today the future industrial achievements that will result from research and development spending in AI is challenging and uncertain, but predicting that the potential future benefits of these innovations will be huge seems quite obvious. A mechanism behind this intuition may be found in a work by Oi (1961). The idea is quite simple: the shape of the profit function of firms is such that when facing a price uncertainty represented by an equiprobable lottery of having a high or a low price, this yields a higher expected profit than the profit a firm gets if it faces the mean price certainly. Hence, assuming that price uncertainty is due to more general uncertainty, then, uncertainty is preferred by firms that are not risk averse.

The goal of this paper is to question this surprising conclusion. The identification of shocks through events constraints can be seen as a sub-family of the (narrative) sign restrictions approach for VARs (Antolín-Díaz & Rubio-Ramírez, 2018). This methodology of identifying shocks is appealing because it imposes restrictions on the structural parameter set that are in general considered "weaker" than more traditional identification hypothesis. Therefore, these restrictions have a higher probability of not being rejected by the data. Since narrative sign restrictions are based on economic appraisals of historical events, it is easy to discuss and hopefully agree on the validity of the proposed restrictions. As stated by Antolín-Díaz & Rubio-Ramírez (2018): *"a single narrative sign restriction may dramatically sharpen and even change the inference of SVARs originally identified via traditional sign restrictions"*. The narrative proposed for each restriction must be convincing enough since one single narrative sign restriction may change the whole results. It seems therefore legitimate to check whether Ludvigson *et al.* (2021)'s conclusions are not driven by just one specific constraint among the set of *event constraints* imposed during the identification strategy and, if so, to question the narrative of this constraint.

We have identified two main shortcomings that could explain the positive correlation between macroeconomic uncertainty and economic activity. Firstly, the choice of the events used in the analysis is questionable. Indeed, the event constraints methodology advocated by Ludvigson *et al.* (2021) imposes a minimum size required on structural uncertainty shocks at specific dates. Examining their list of events, a restriction on the structural macroeconomic uncertainty shock in 1970:12 is selected. This choice is surprising given that the uncertainty indexes do not exhibit a peak at this date. This date corresponds to the beginning of the unsustainability period due to the collapse of the Bretton Woods system according to the authors. By removing one by one the restrictions used in their model, we obtain the positive effect of macroeconomic uncertainty highlighted by these authors, only if the constraint related to a high structural shock of macroeconomic uncertainty on 1970:12 is not completely removed from the analysis. Therefore, we show that the positive effect estimated is only related to this specific constraint and not to the three other constraints that concern the macroeconomic uncertainty. We get the same results starting the sample at 1972:01 to remove this constraint in another way.

Secondly, some significant uncertainty shocks have not been taken into account in their model. Major uncertainty shocks such as the 09/11 attacks, the Russian financial crisis and LTCM in 1998 for financial uncertainty have been omitted in the set of restrictions considered by Ludvigson *et al.* (2021). We add new restrictions to take into account the 09/11 attacks and the Russian financial crisis which are often cited as uncertainty shocks in the literature (See, among many others, Bloom, 2009; Baker *et al.*, 2016; Larsen, 2021; Himounet, 2022).

Adding these new restrictions, we no longer find the positive effect of macroeconomic uncertainty shocks. We get a negative effect showing that their results seem not to be robust to the choice of events related to structural uncertainty shocks. In the end, the controversial result of a positive effect of macroeconomic uncertainty on economic activity does not yet seem to be proven. Whether financial or macroeconomic, there is no evidence allowing for the rejection of the hypothesis that uncertainty has a negative impact on economic activity.

The rest of this paper is organized as follows. Section 2 presents a brief review on how to identify shocks with a SVAR framework. Section 3 questions the narrative events constrains selected by Ludvigson *et al.* (2021) and their impact on the economic activity. Section 4 presents results adding new constraints. In section 5, some robustness checks are analyzed. The last section presents conclusions.

2 Identifying Structural Uncertainty Shocks

2.1 A Brief Review of the Literature

Usually, structural VAR models (SVAR) have been applied to investigate the impact of uncertainty on macroeconomic activity. Consider the SVAR(p) model:

$$X_t = A_0 + \sum_{j=1}^{p} A_j X_{t-j} + B\, e_t \tag{1}$$

where X_t denotes the vector of endogenous variables. e_t denotes a vector of zero-mean, serially uncorrelated structural shocks with identity covariance matrix:

$$E[e_t e_t'] = I \tag{2}$$

The corresponding reduced-form $VAR(p)$ is defined as follows:

$$X_t = A_0 + \sum_{j=1}^{p} A_j X_{t-j} + \eta_t \tag{3}$$

$$\eta_t = B\ e_t \tag{4}$$

where η_t denotes a vector of zero-mean, serially correlated shocks with a covariance matrix Ω:

$$E[\eta_t \eta_t'] = \Omega \tag{5}$$

In the SVAR model, the key point is to identify structural shocks. The traditional approach is to use a recursive scheme imposing the contemporaneous matrix B to be the lower-triangular matrix of the Cholesky decomposition of Ω:

$$\Omega = BB' \tag{6}$$

Other identification procedures can be applied. Ramey (2016) and Rossi (2021) review the different methodologies identifying structural shocks in a SVAR model. These strategies of identification include different schemes on contemporaneous restrictions, heteroskedasticty-based identification, sign-restrictions, narrative methods, high frequency identification, proxy SVARs with external instruments, long term restrictions, factor-augmented VARs and DSGE models.[2] Recently, new methodologies have been developed in the empirical literature such as Inoue & Rossi (2021) with the functional shocks in the VAR and Ludvigson *et al.* (2021) with events constraints. In the following, we will discuss in further details the framework advocated by Ludvigson *et al.* (2021) to identify structural shocks.

2.2 Identifying shocks with *events constraints*

Following Ludvigson *et al.* (2021), we denote $X_t = (U_{Mt}, Y_t, U_{Ft})'$ the vector of endogenous variables described in (1). U_{Mt} denotes the macroeconomic uncertainty index, Y_t denotes the industrial production in log-level and U_{Ft} denotes the financial uncertainty index. The macroeconomic uncertainty index and the financial uncertainty index have been estimated applying the methodology of Jurado *et al.* (2015).[3] The covariance matrix Ω can be decomposed according

[2]See Ramey (2016) and Rossi (2021) for a detailed presentation of these SVAR identification strategies.

[3]The correlation between both uncertainty indexes is close to 0.6 with a p-value equal to 0. The aim of this paper is to question the results of Ludvigson *et al.* (2021) examining their new SVAR identification procedure and

to the Cholesky decomposition such that $\Omega = PP'$. P denotes the lower-triangular matrix of the Cholesky decomposition. The structural shocks $e_t = (e_{Mt}, e_{Yt}, e_{Ft})'$ are related to the reduced form innovations $\eta_t = (\eta_{Mt}, \eta_{Yt}, \eta_{Ft})'$ by the relationship: $B\ e_t = \eta_t$. The matrix B is a 3×3 matrix with 9 parameters. The reduced-form covariance structure of η_t only provides $n(n+1)/2 = 6$ restrictions. Additional restrictions have to be imposed to identify the effects of the structural shocks e_t on the endogenous variables in X_t. Otherwise, the model is under-identified and many solutions can satisfy the covariance restriction : $\Omega = BB'$. Let $\hat{\mathcal{B}}$ denotes the set of solutions named *unconstrained set* such that:

$$\hat{\mathcal{B}} = \{B = \hat{P}Q : Q \in \mathbb{O}_n, diag(B) \geq 0, \Omega = BB'\} \tag{7}$$

where $\mathbb{O}_n$ denotes the set of $n \times n$ orthogonal matrices ($QQ' = I_n$). By construction:

$$E[\eta_t \eta_t'] = BB' = \hat{P}Q\left(\hat{P}Q\right)' = \hat{P}QQ'\hat{P}' = \hat{P}\hat{P}' = \hat{\Omega} \tag{8}$$

To construct the set $\hat{\mathcal{B}}$, the algorithm is initialized by setting $B = P$. Then, they rotate B by randomly drawing 1.5 million matrices Q. Each rotation is performed by drawing a $n \times n$ matrix M of $\mathcal{N}(0, I_n)$. Q is taken to be the orthogonal matrix in the QR decomposition of M and R denotes an upper-triangular matrix. By construction, the covariance restriction $\Omega = BB'$ is satisfied. Let $e_t(B) = B^{-1}\eta_t$ be the shocks implied by a matrix $B \in \hat{\mathcal{B}}$ for a given η_t. 1.5 million different B imply 1.5 million values of $e_t(B)$ for $t = 1, \ldots, T$. Thus, we get 1.5 million time series of e_{Mt}, 1.5 million time series of e_{Yt} and 1.5 million time series of e_{Ft} for $t = 1, \ldots, T$.[4]

The identification of uncertainty shocks in the SVAR will be based on imposing some *event constraints* and external variable constraints on these 1.5 millions of series. *Event constrains* restrict the structural shocks based on a reading of the times throughout history. The structural shocks must be consistent with our *ex-post* understanding of historical events. For *event constraints* selection, the authors have applied a mix between a "pure" narrative approach

not the potential similarities between their both uncertainty indexes. The problem of similarities between their macroeconomic and financial uncertainty indexes has been discussed by Himounet (2022).

[4]We apply the MATLAB program provided by Ludvigson *et al.* (2021) in their replication files.

framework and restrictions determined by the study of of the maximum of structural shocks $e_t = (e_{Mt}, e_{Yt}, e_{Ft})'$. In their simulations, the maximum values over the 1.5 millions rotations are located on the following dates. The date on which the structural financial uncertainty shock e_{Ft} most often reaches its maximum is 2008:09 corresponding to the collapse of Lehman Brothers. The second date is 1987:10 corresponding to the Black Monday. The date where the structural macroeconomic uncertainty shock e_{Mt} most often reaches its maximum is again 2008:09. The second is 1970:12 corresponding to the beginning of the unsustainability following the collapse of the Bretton Woods system according to the authors. Their study of the maximum in structural uncertainty shocks allows to define some *event constraints* in their application imposing structural uncertainty shocks to be strong at these specific dates.

2.3 Application and Baseline Results of Ludvigson *et al.* (2021)

In their SVAR model, Ludvigson *et al.* (2021) have defined their *event constraints* as follows:

1. $\bar{g}_{E1} : e_{F\tau_1} \geq \bar{k_1}$ at $\tau_1 = 1987:10$ (Black Monday)
2. $\bar{g}_{E2} : \left(e_{F\tau_2} \geq \bar{k_2}\right)$ or $\left(e_{M\tau_2} \geq \bar{k_3}\right)$ at $\tau_2 = 2008:09$ (Lehman Brothers)
3. $\bar{g}_{E3} : e_{M\tau_3} \geq \bar{k_4}$ at $\tau_3 = 1970:12$ (Bretton Woods)
4. $\bar{g}_{E4} : 0 \geq \sum\limits_{t=\tau_4} e_{Yt}$ for $\tau_4 \in [2007:12, 2009:06]$ (Great Recession)
5. $\bar{g}_{E5} : e_{M\tau_5} \geq 0$ and $e_{F\tau_5} \geq 0$ at $\tau_5 = 1979:10$ (Volcker)
6. $\bar{g}_{E6} : e_{M\tau_6} \geq 0$ and $e_{F\tau_6} \geq 0$ at $\tau_6 \in [2011:07, 2011:08]$ (Debt Ceiling Crisis)

The first condition requires that the financial uncertainty shock of October 1987 corresponding to the black Monday must be large exceeding the threshold $\bar{k_1}$. The second condition imposes that either the financial uncertainty shock or the macroeconomic uncertainty shock (or both) in September 2008 corresponding to the collapse of Lehman Brothers be large exceeding the thresholds $\bar{k_2}$ and $\bar{k_3}$ respectively. The third condition requires that the macroeconomic uncertainty shock found in December 1970 must be large exceeding the threshold $\bar{k_4}$. These three constraints have been determined by the study of the maximum in structural shocks e_t that we have mentioned previously. The next constraints are more related to narrative restrictions regarding historical events. The fourth condition means that the cumulation of real activity shocks during the Great Recession must be negative meaning that their sum may not be above average. The fifth condition imposes restrictions on both types of uncertainty shocks. At the month of October 1979 with the Volcker experiment, both types of uncertainty shocks must be positive. The last condition imposes restrictions on two months: 2011:07 and 2011:08 corresponding to the 2011 debt-ceiling crisis. Both types of uncertainty shocks must be positive at these months. The six event constraints $\bar{g}_{E1}, \bar{g}_{E2}, \bar{g}_{E3}, \bar{g}_{E4}, \bar{g}_{E5}, \bar{g}_{E6}$ can be represented by a system of inequality constraints on B:

$$\bar{g}_E \left(e_t \left(B \right); \bar{\tau}, \bar{k} \right) \geq 0 \tag{9}$$

where $\bar{k} = \left(\bar{k_1}, \bar{k_2}, \bar{k_3}, \bar{k_4} \right) > 0$ and $\bar{\tau} = (\bar{\tau_1}, \bar{\tau_2}, \bar{\tau_3}, \bar{\tau_4}, \bar{\tau_5}, \bar{\tau_6})$.

According to Ludvigson *et al.* (2021), this approach differs from the narrative approach given that the same SVAR is applied to identify all shocks simultaneously unlike the previous empirical studies which have used a two-step procedure that identifies some shocks ahead of others. Other constraints have been proposed from correlation with external variables. According to Ludvigson *et al.* (2021), external variables can facilitate the identification in the VAR when economic reasoning implies they should be informative about the shocks. The correlations between the external variables and structural uncertainty shocks have been used to generate additional inequality constraints:

1. $\bar{g}_{C1} : 0 \geq corr \left(e_{jt}, S_{1t} \right), j = M, F$

2. $\bar{g}_{C2} : corr \left(e_{jt}, S_{2t} \right) \geq 0, j = M, F$

where S_1 denotes the CRSP value-weighted stock market index which is considered as a measure of stock market returns and S_2 denotes the real price of gold in log difference.

The first correlation constraint requires that uncertainty shocks must be negatively correlated with stock market returns. The second correlation constraint means that both types of uncertainty shocks must be positively correlated with the variation of the real price of gold that is considered as a safe asset by investors. The correlation constraints $\bar{g}_{C1}, \bar{g}_{C2}$ can be represented by a system of inequality constraints on B:

$$\bar{g}_C\left(e_t\left(B\right);S\right) \geq 0 \tag{10}$$

The matrices B satisfying the following system of inequalities are retained :

$$\hat{\mathcal{B}} = \{B = \hat{P}Q : Q \in \mathbb{O}_n, diag(B) \geq 0, \Omega = BB', \bar{g}_E\left(e_t\left(B\right);\bar{\tau},\bar{k}\right) \geq 0, \bar{g}_C\left(e_t\left(B\right);S\right) \geq 0\} \tag{11}$$

A crucial point is to estimate the parameters $\bar{k_1}$, $\bar{k_2}$, $\bar{k_3}$, $\bar{k_4}$. For illustration, we will describe the first condition $\bar{g}_{E1} : e_{F\tau_1} \geq \bar{k_1}$ at $\tau_1 = 1987 : 10$ (Black Monday). Given that 1.5 million time series of e_{Ft} have been estimated, we get 1.5 million values for e_{Ft} at $t = 1987 : 10$. According to Ludvigson *et al.* (2021), the threshold $\bar{k_1}$ should correspond to the $75th$ percentile value of e_{Ft} at $t = 1987 : 10$ which is equal to 4.1634. The same procedure has been applied for $\bar{k_2}$, $\bar{k_3}$, $\bar{k_4}$ at their respective dates. For $\bar{k_2}$, they take the $75th$ percentile value of e_{Ft} at $t = 2008 : 09$ which is equal to 4.5672. For $\bar{k_3}$, they take the $75th$ percentile value of e_{Mt} at $t = 2008 : 09$ which is equal to 4.7314. For $\bar{k_4}$, they take the $75th$ percentile value of e_{Mt} at $t = 1970 : 12$ which is equal to 4.048. These parameters can be interpreted as the minimum size required of the structural shocks for the events associated with the constraints.

At the beginning, there was 1.5 million matrices B. Imposing the restrictions of Ludvigson *et al.* (2021) in the data will then suppress a number of matrices B. For example, imposing the first restriction $\bar{g}_{E1}$ will reduce the number from 1.5 millions to 375000. Adding the other constraints mentioned previously to get the full set of restrictions described by the system (11), the number of matrices B is extremely reduced. Indeed, the number of matrices B satisfying the full set of restrictions is equal to 169. Ludvigson *et al.* (2021) estimate as many impulse response functions as the number of matrices B retained. Therefore, 169 impulse response functions are estimated. To compute the impulse response functions, we can write the VAR model described by (1) in its moving average (MA) representation:

$$X_t = \mu + \sum_{i=0}^{\infty} \phi_i \, B e_{t-i} \tag{12}$$

For each matrix B satisfying the full set of constraints, impulse response functions at a horizon h after a shock of the jth variable are computed such that:

$$\frac{\delta \, X_{t+h}}{\delta \, e_{jt}} = \phi_h \, b^j \tag{13}$$

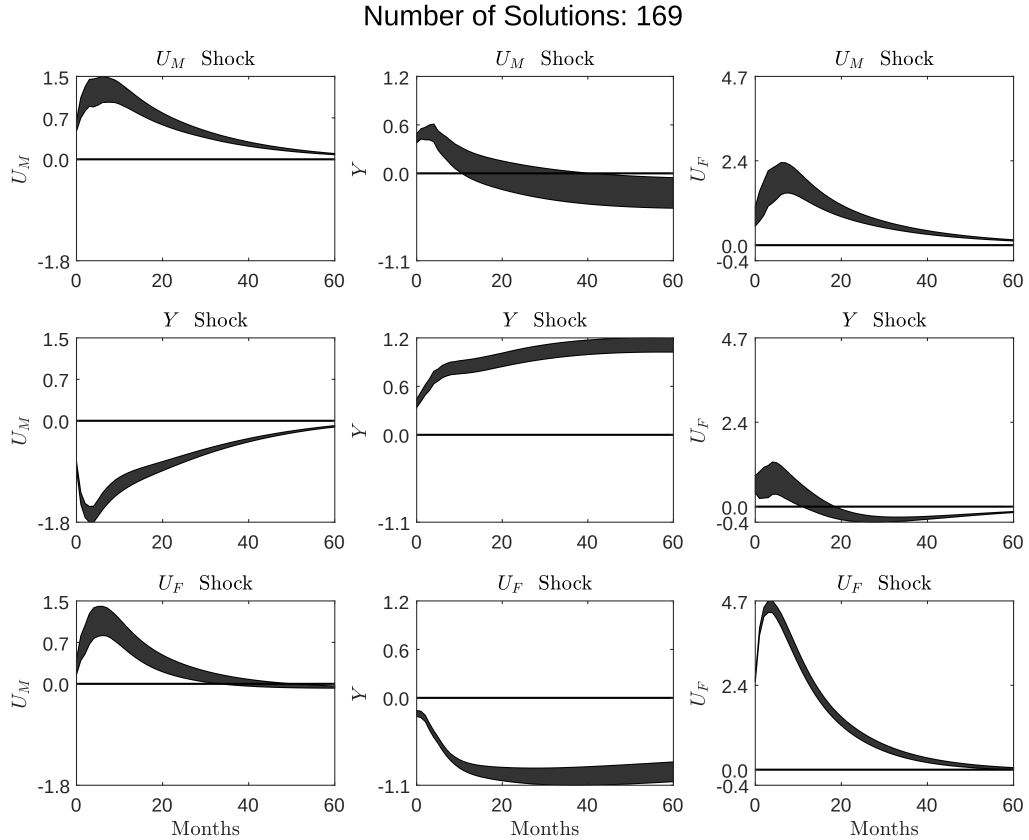
where b^j denotes the jth column of the matrix B.[5]

Figure 1 reproduces the impulse response functions of Ludvigson *et al.* (2021). For each panel, for each horizon h, the shaded area represents IRFs for all values among the 169 matrices B satisfying the full set of constraints described by the system (11). The lower bound of the shaded area represents the minimum value among the 169 IRF values and the upper bound represents the maximum value among the 169 IRF values. It means that the IRF value can fluctuate between these both values. For example, examining the effect of a financial uncertainty shock on industrial production (lower middle panel) at the horizon $h = 20$, the lower bound of the shaded area is equal to -1.06 corresponding to the minimum value among the 169 possible values. The upper bound of the shaded area is equal to -0.89 corresponding to the maximum value among the 169 possible values. Therefore, the IRF value of a financial uncertainty shock on industrial production at the horizon $h = 20$ fluctuates between -1.06 and -0.89 highlighting a negative effect for this horizon. An increase in macroeconomic uncertainty rises financial uncertainty (upper right panel) and inversely (lower left panel). The results indicate that financial uncertainty shocks have a negative impact on industrial production which is very persistent for more than 5 years (lower middle panel). However, macroeconomic uncertainty shocks have a positive effect on industrial production (upper middle panel) breaking the empirical consensus on the negative effect of uncertainty. The effect is no longer interpretable after 12 months as the zero value belongs to the shaded area.[6]

[5] When $h = 0$, $\phi_h = I_n$.

[6] We don't find any matrices B satisfying the full set of restrictions if we run their model on a longer sample: 1960:07-2019:12. Therefore, we cannot compute the IRFs.

Figure 1: Impulse Response Functions of Ludvigson *et al.* (2021)



Notes: The figure shows results from the identified set for the system $X_t = (U_{Mt}, Y_t, U_{Ft})'$ using the full set of constraints described in (11) with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the full set of constraints described in (11). The sample spans the period 1960:07 to 2015:04.

3 How to select events constraints restrictions ?

In this section, we will question the events constraints put forward by Ludvigson *et al.* (2021) and their effect on the results of a positive impact of uncertainty.

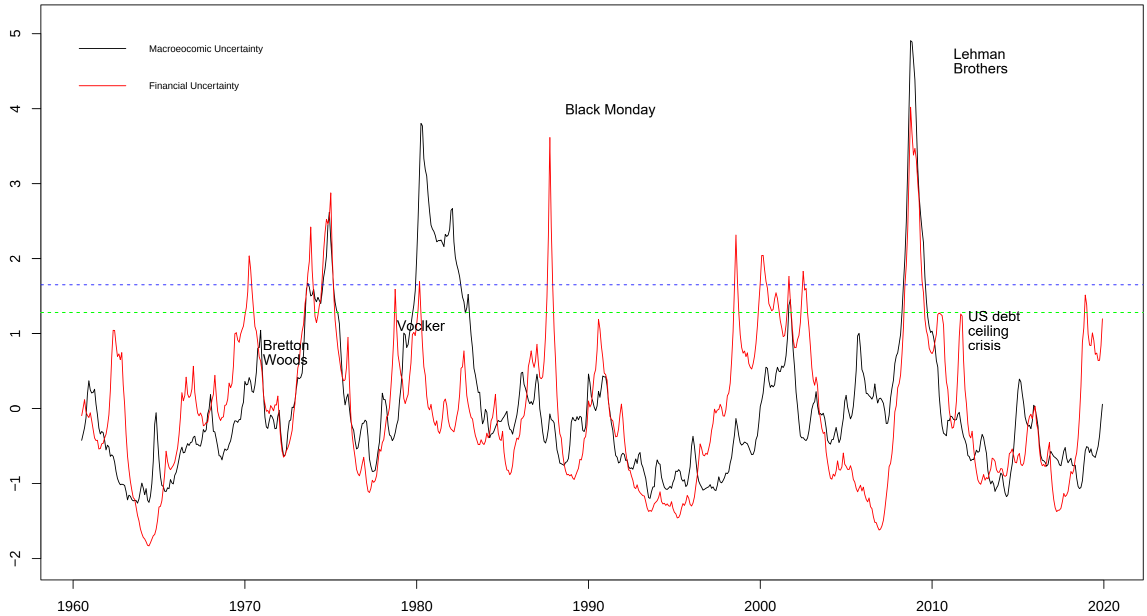
3.1 The collapse of the Bretton Wood system

Undoubtedly, in the stimulating chase of a positive effect of uncertainty, the work of Ludvigson *et al.* (2021) is very interesting and innovative. However, their analysis suffers from some caveats. Our goal in this section is to extend their methodology. The first discussion concerns the choice of the constraints proposed by Ludvigson *et al.* (2021). Even if the approach of the study of the maximum in structural shocks e_t can be interesting, it does not really correspond to the narrative approach. The first three *event constraints* are not based on a reading of uncertainty indexes contrary to Caggiano *et al.* (2021) and Larsen (2021) which have examined the peaks of their uncertainty indexes. In his seminal paper, Bloom (2009) considers an uncertainty peak as significant at the 5% level if the uncertainty index exceeds 1.65 standard deviation above the mean. The restrictions of Caggiano *et al.* (2021) are based on the dates that Bloom (2009) has identified following the threshold of 1.65. Examining the list of *event constraints* of Ludvigson *et al.* (2021), some restrictions on the high structural uncertainty shocks as the collapse of Lehman Brothers in 2008 and the Black Monday in 1987 can be justified following the criterion of Bloom (2009). The macroeconomic uncertainty shock and the financial uncertainty shock associated with Lehman Brothers exceed the threshold of 1.65 (Figure 2). It is the same for the financial uncertainty shock associated with the Black Monday. However, the choice of the shock restriction on the structural macroeconomic uncertainty shock in 1970:12 can be surprising. This date should correspond to the beginning of the unsustainability of the Bretton Woods system according to the authors. Examining uncertainty indexes in Figure 2, we note that the level of macroeconomic uncertainty is not very high at this date and it does not exceed the threshold of 1.65.[7] The same comment is true for the financial uncertainty index at this date. This observation raises questions about the justification of this constraint despite the interesting approach of the study of the maximum in e_t. How will the results change if we remove the constraint $\bar{g}_{E3}$ related to Bretton Woods ?

Removing the constraint $\bar{g}_{E3}$, the number of matrices B increases to 1101. The IRF bands are larger than previously (Figure 3). We have the same results about the impact of financial uncertainty shocks on industrial production with a negative effect after 11 months. However, about the effect of macroeconomic uncertainty shock on industrial production, it is difficult to assign an interpretation to the shock since 0 is between the minimum and the maximum of the IRFs bands (upper middle panel). Could this constraint explain their result on the positive effect of macroeconomic uncertainty ? To try to answer this question, we run the model of

[7]The shock on 1970:12 also does not exceed the threshold of 1.28 if we are at the 10% level.

Figure 2: Macroeconomic Uncertainty VS Financial Uncertainty



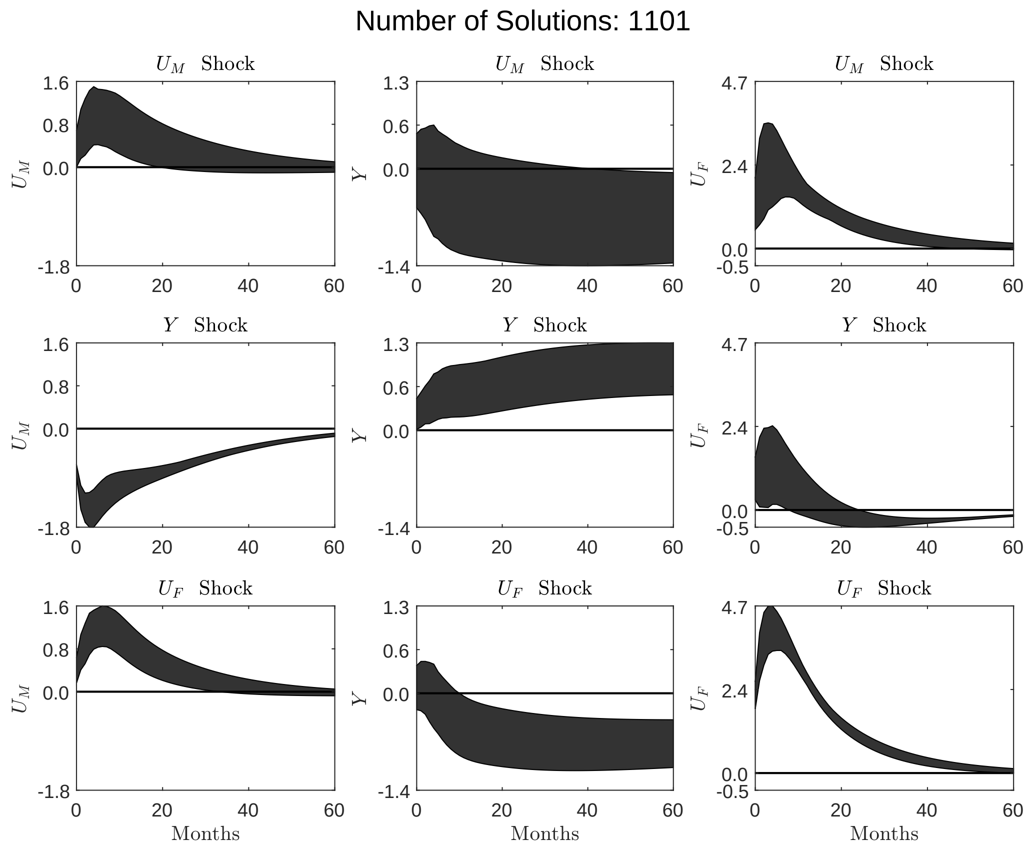
Source: Ludvigson *et al.* (2021)
Notes: The measures are standardized. The horizontal dashed blue line represents the threshold 1.65. The horizontal dashed green line represents the threshold 1.28.

Ludvigson *et al.* (2021) removing one by one the different event constraints. We run the model removing $\bar{g}_{E1}$ and maintaining $\bar{g}_{E2}$, $\bar{g}_{E3}$, $\bar{g}_{E4}$, $\bar{g}_{E5}$, $\bar{g}_{E6}$. Then, we run the model removing $\bar{g}_{E2}$ and maintaining $\bar{g}_{E1}$, $\bar{g}_{E3}$, $\bar{g}_{E4}$, $\bar{g}_{E5}$, $\bar{g}_{E6}$. We repeat the same procedure for the constraints $\bar{g}_{E4}$, $\bar{g}_{E5}$, $\bar{g}_{E6}$. We always get their positive effect of macroeconomic uncertainty showing that the constraint related to Bretton Woods can explain their positive effect. To add another proof, we run their model on a subsample: 1972:01-2015:04. Using this subsample, we start after the events related to Bretton Woods and therefore, we remove the restriction $\bar{g}_{E3}$ in another way. We get a slightly negative effect of financial uncertainty shocks and macroeconomic uncertainty shocks on industrial production but in the long term (Figure 4).[8]

It is obvious that the collapse of the Bretton Woods system was a turning point for the world economy and, thus, its end can be inserted in narrative restrictions. However, the real end of the

[8]We get a negative effect of macroeconomic uncertainty shocks using the sample 1972:01-2019:12.

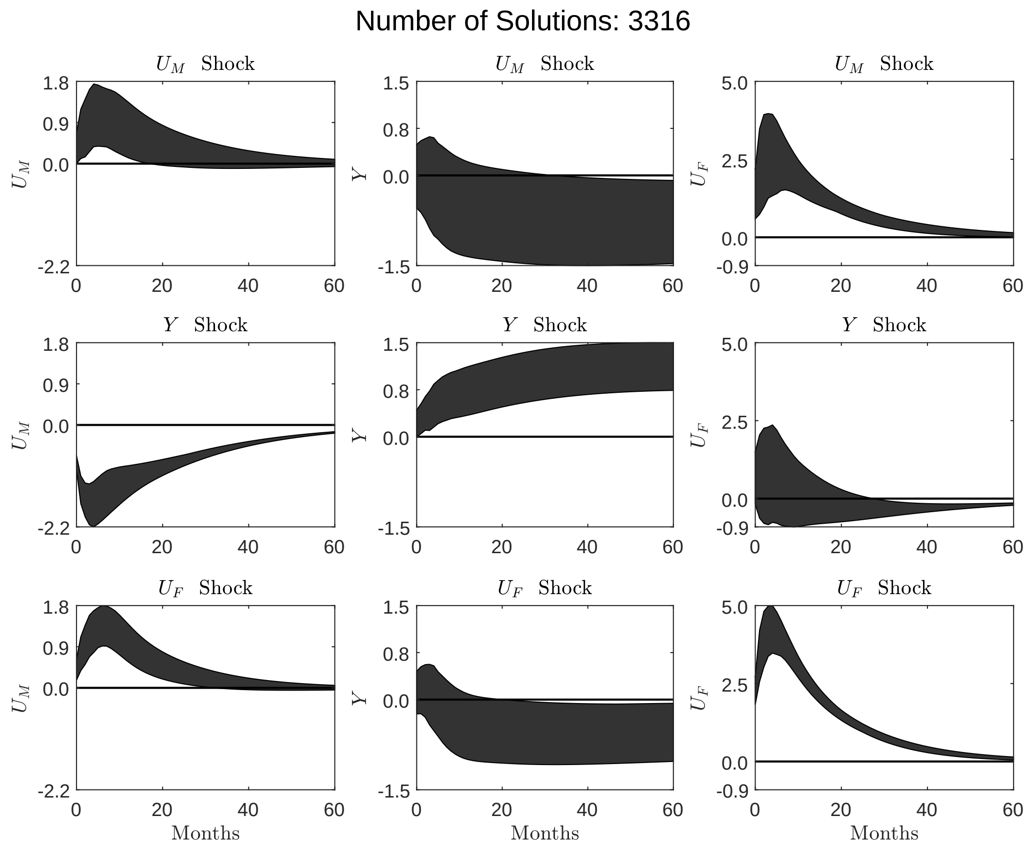
Figure 3: Impulse Response Functions removing $\bar{g}_{E3}$



Notes: The figure shows results from the identified set for the system $X_t = (U_{Mt}, Y_t, U_{Ft})'$ using the set of constraints described in (11) but removing $\bar{g}_{E3}$ with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the set of constraints. The sample spans the period 1960:07 to 2015:04.

Bretton Woods system was announced in August 1971 by Richard Nixon with the *Nixon shock*. Therefore, to really take into account Bretton Woods, we must modify the constraint $\bar{g}_{E3}$ taking $\tau_3 =$1971:08 instead of 1970:12. We get a negative effect of macroeconomic uncertainty shocks on industrial production (Figure 5) instead of the positive effect highlighted by Ludvigson *et al.* (2021). These findings show that their positive effect of macroeconomic uncertainty is not robust modifying their constraint related to the date of the Bretton Woods. We don't find any solutions expanding the sample to 2019:12.

Figure 4: Impulse Response Functions using the period 1972:01 to 2015:04



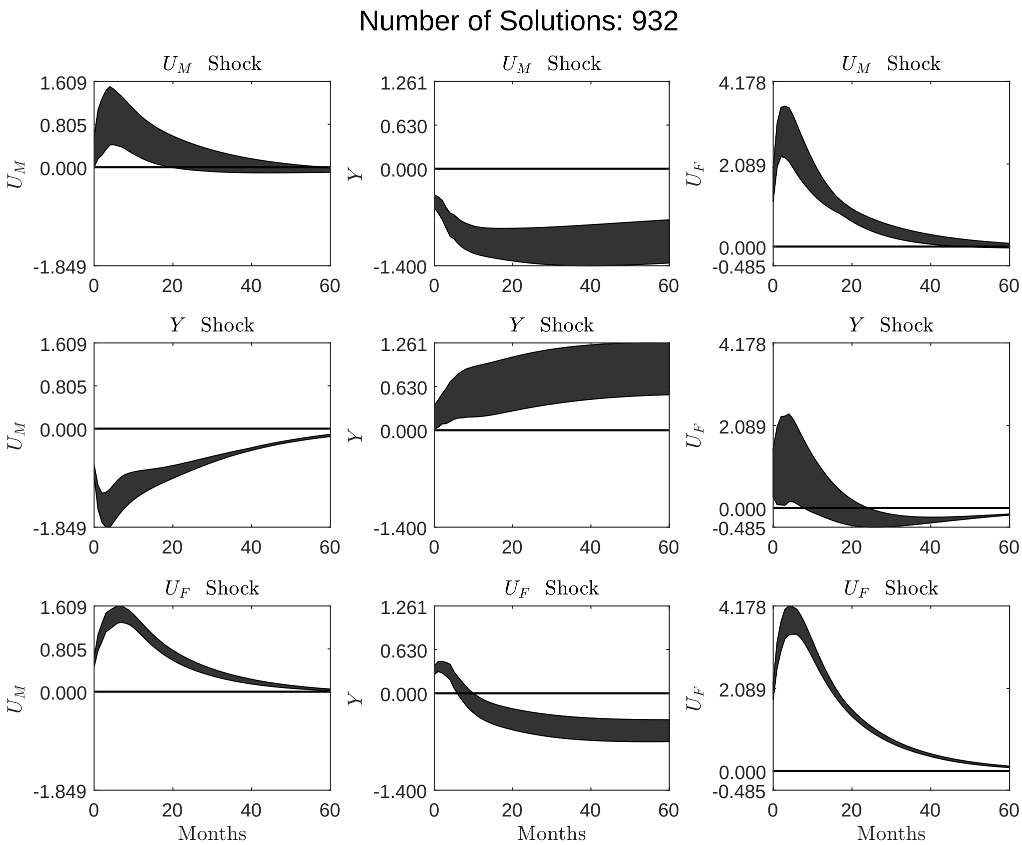
Notes: The figure shows results from the identified set for the system $X_t = (U_{Mt}, Y_t, U_{Ft})'$ using the set of constraints with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the set of constraints. The sample spans the period 1972:01 to 2015:04.

3.2 Real Uncertainty Index

Following Ludvigson *et al.* (2021), we replace the macroeconomic uncertainty index with their real uncertainty index (U_R) which is a sub-index of macroeconomic uncertainty. The macroeconomic uncertainty index of Ludvigson *et al.* (2021) is estimated with the methodology of Jurado *et al.* (2015) applying a set of 132 macroeconomic time series which are taken from the McCracken database.[9] These 132 macroeconomic time series can be divided in eight different groups: "Output and Income", "Labor Market", "Housing", "Consumption, Orders and Inventories", "Money and Credit", "Interest and Exchange Rates", "Prices" and stock market indexes.

[9] A detailed list of the time series is available on the McCracken website.

Figure 5: Impulse Response Functions modifying the constraint $\bar{g}_{E3}$



Notes: The figure shows results from the identified set for the system $X_t = (U_{Mt}, Y_t, U_{Ft})'$ using the set of constraints with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. We modify the constraint $\bar{g}_{E3}$ taking $\tau_3 = 1971:08$. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the set of constraints. The sample spans the period 1960:07 to 2015:04.

Ludvigson *et al.* (2021) have pointed out that their macroeconomic uncertainty index can fluctuate due to uncertainty in real activity variables such as output and unemployment but also due to price variables or financial market variables. To separate the fluctuations due to real activity variables from the fluctuations due to price and financial variables, these authors compute a real uncertainty index aggregating 73 time series among the 132 used (Figure A1). These 73 time series are related to the first four groups corresponding to real activity : output and income, labor market, housing (constructions) and the group related to consumption, orders and inventories. Using their full set of constraints, Ludvigson *et al.* (2021) have found a positive effect of real uncertainty on industrial production which is more persistent than the positive effect of macroeconomic uncertainty : in Figure A2 are reproduced their results and we get the positive effect of real uncertainty. Removing the constraint $\bar{g}_{E3}$ related to Bretton Woods, the positive effect of real uncertainty is no more detected as the zero value belongs to the interval (see Figure A3).[10] However, the existence of this constraint can be justified since the real uncertainty index exhibits a spike on 1970:12 where the level exceeds 1.65 standard deviations above the mean. We repeat the procedure taking $\tau_3 = 1971 : 08$ instead of $1970 : 12$ in the restrictions as previously and we also find that real uncertainty shocks have a negative impact on industrial production (Figure A4). We get the same results expanding the sample to 2019:12.

The fact that the positive effect of macroeconomic uncertainty depends uniquely on the $\bar{g}_{E3}$ constraint, that is about BW, is surprising. When looking at the possible theoretical explanations of a positive effect of uncertainty proposed by the authors, they refer to the "growth option" theory and to several works by Oi (1961) and others. The main intuitions and mechanisms behind these theoretical arguments are based either on (i) the hope of generating huge profits in the future by investing in a radically new technology despite its precise potential outcomes remains uncertain or on (ii) the shape of the profit function that yields much higher profit with a high price than a low price thus making the price uncertainty of having the high or the low price with equiprobability more rewarding than having the mean price for sure. The link between those two explanations and the economic effects of the end of the Bretton Woods system are not straightforward.

Nevertheless, the fact that changing the date of the $\bar{g}_{E3}$ constraint by only a few months changes the result so drastically is puzzling. Even more puzzling is that trying to solve this puzzle, we ran some robustness checks (see section 5.1) which for we have just changed the constraint by one month, either November 1970 or January 1971 instead of December 1970. Again, the positive effect totally vanishes to be replaced by a strong significant negative effect.

Another element is worth mentioning. When looking at the different variables that enter the real uncertainty index of Ludvigson *et al.* (2021), we observe a surge of growth in this

[10] Using the subsample 1972-2015, we have the same results. We can't interpret the effect of real uncertainty shocks on industrial production.

specific month of December 1970 (see Appendix B) which is a catch up after the mild recession of 1969-1970. Hence, just keeping uncertainty peaks for this specific month may artificially associate a high uncertainty to a very specific episode of strong growth. This may explain the positive sign found with the constraint on December 1970. Moreover, we shall remind that the uncertainty measure of Ludvigson *et al.* (2021) is based on the residuals of econometric specifications, that is the part that is unexplained by the model estimated. As a matter of fact, since the 1969-1970 recession has lasted 11 months, from December 1969 to November 1970, the most probable forecast for the following month was another month of recession which is not what happened. So the strong catch up in growth of December 1970 also constitutes an important forecast error (see Appendix B). Therefore, the strong growth and strong uncertainty indeed appeared in December 1970, but their common cause is the recession that occurred previously. The causality does not exist and, to be fair, this is in line with one of the main results of Ludvigson *et al.* (2021): the macroeconomic uncertainty is not causal, but rather an effect of recession, instead of the financial uncertainty that can be a cause of recession.

4 Introducing New Event Constraints

Except for the constraint related to 1970:12, other constraints on high uncertainty shocks like the collapse of Lehman Brothers, the Black Monday in 1987 can be justified as uncertainty indexes exhibit spikes at these particular dates. However, other uncertainty shocks have not been taken into account like the 09/11 attacks and the Russian financial crisis and Long Term Capital Management in 1998 examining the uncertainty indexes. These shocks are often cited as uncertainty shocks in this literature. We don't find any justifications for not including these significant uncertainty shocks in the analysis. Applying the methodology of *event constraints*, Caggiano *et al.* (2021) and Larsen (2021) have inserted restrictions related to uncertainty shocks at the 09/11 attacks and the Russian financial crisis because their uncertainty variables exhibit spikes at these specific dates. Are the results of a positive effect of uncertainty robust if we add new constraints? We will try to answer this question defining additional constraints as follows:

- $\bar{g}_{E7} : e_{M\tau_7} \geq \bar{k_5}$ at $\tau_7 = 2001 : 09$ (09/11 attacks)

- $\bar{g}_{E8} : e_{F\tau_8} \geq \bar{k_6}$ at $\tau_8 = 1998:08$ (Russian Crisis and LTCM)

The condition $\bar{g}_{E7}$ requires that the structural macroeconomic uncertainty shock associated with the 09/11 attacks must be large exceeding the parameter $\bar{k_5}$. The condition $\bar{g}_{E8}$ means that the structural financial uncertainty shock associated with Russian financial crisis and LTCM must exceed the parameter $\bar{k_6}$. We add the new restrictions to the full set of constraints of Ludvigson *et al.* (2021). The parameters $\bar{k_5}$ and $\bar{k_6}$ are taken to their 75th-percentile values of the unconstrained set like previously. The $75th$ percentile value of e_{Mt} at $t = 2001:09$ is equal to 2.0701 and the $75th$ percentile value of e_{Ft} at $t = 1998:08$ corresponds to 2.9724. However, we don't find any matrices B satisfying the new full set of constraints. We separately insert these constraints in their model. We introduce the condition $\bar{g}_{E7}$ in the full set of constraints of Ludvigson *et al.* (2021) taking the 75th-percentile value of e_{Mt} at $t = 2001:09$. However, we don't find any matrices B and thus, we cannot compute the IRFs. We alleviate this constraint taking the parameter $\bar{k_5}$ to the median value of the unconstrained set (1.3823) and we get the same set of 169 matrices B. Adding the constraint $\bar{g}_{E8}$ in the full set of restrictions of Ludvigson *et al.* (2021), we don't find any solutions.

We repeat the procedure with our new constraints but removing the constraint $\bar{g}_{E3}$ related to Bretton Woods. The parameters $\bar{k_5}$ and $\bar{k_6}$ are taken to the median values and the 75th-percentile values of the unconstrained set respectively.[11] We retain 93 matrices B satisfying the constraints. The striking result we obtain is that macroeconomic uncertainty shocks have a negative impact with the decline in industrial production (Figure 6, upper middle panel). This negative effect is very persistent over the years. These findings show that the SVAR identification strategy of these authors is not robust according to the chosen constraints.[12] Expanding the sample to 1960:07-2019:12, we get just one solution B where we find a negative effect of macroeconomic uncertainty.[13]

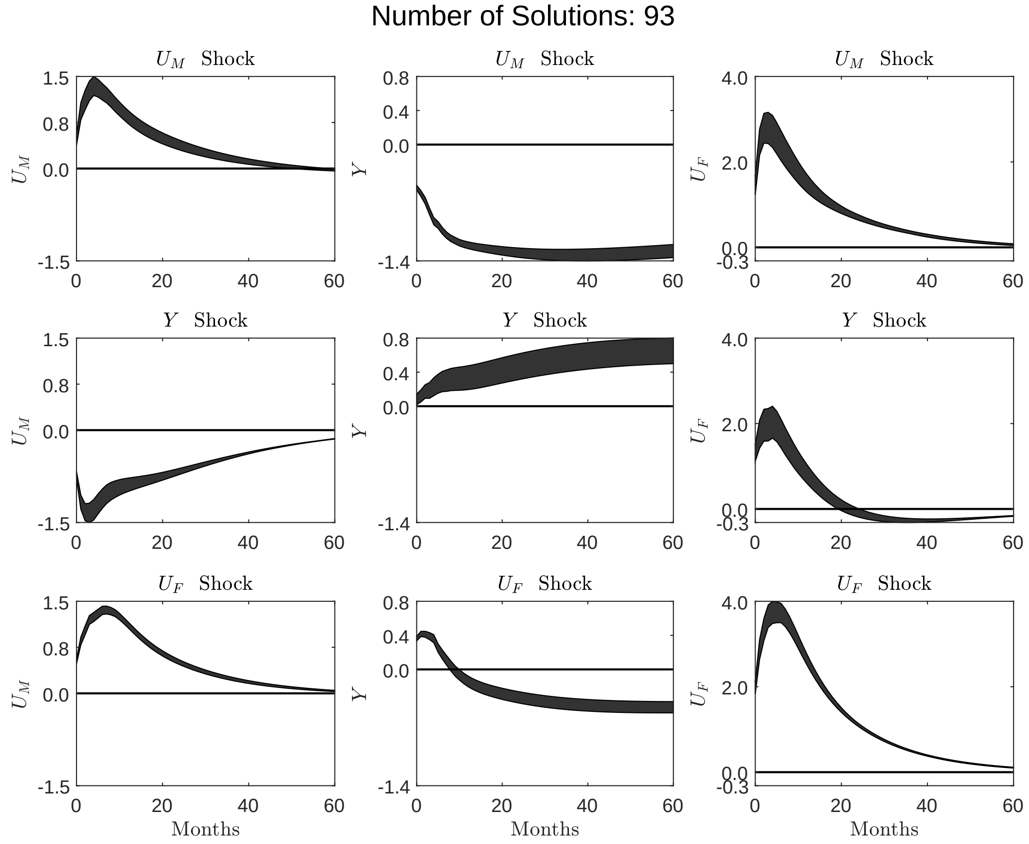
As previously, to really take into account the end of the Bretton Woods system, we keep the constraint $\bar{g}_{E3}$ but taking $\tau_3 = 1971:08$ and we add our constraints $\bar{g}_{E7}$ and $\bar{g}_{E8}$. We

[11] We don't find any solutions taking the 75th-percentile value of e_{Mt} at $t = 2001:09$

[12] The results are robust applying the real uncertainty index.

[13] For this case, the parameters $\bar{k_5}$ and $\bar{k_6}$ are taken to their median values. Otherwise, we cannot compute the IRF.

Figure 6: Impulse Response Functions using different constraints

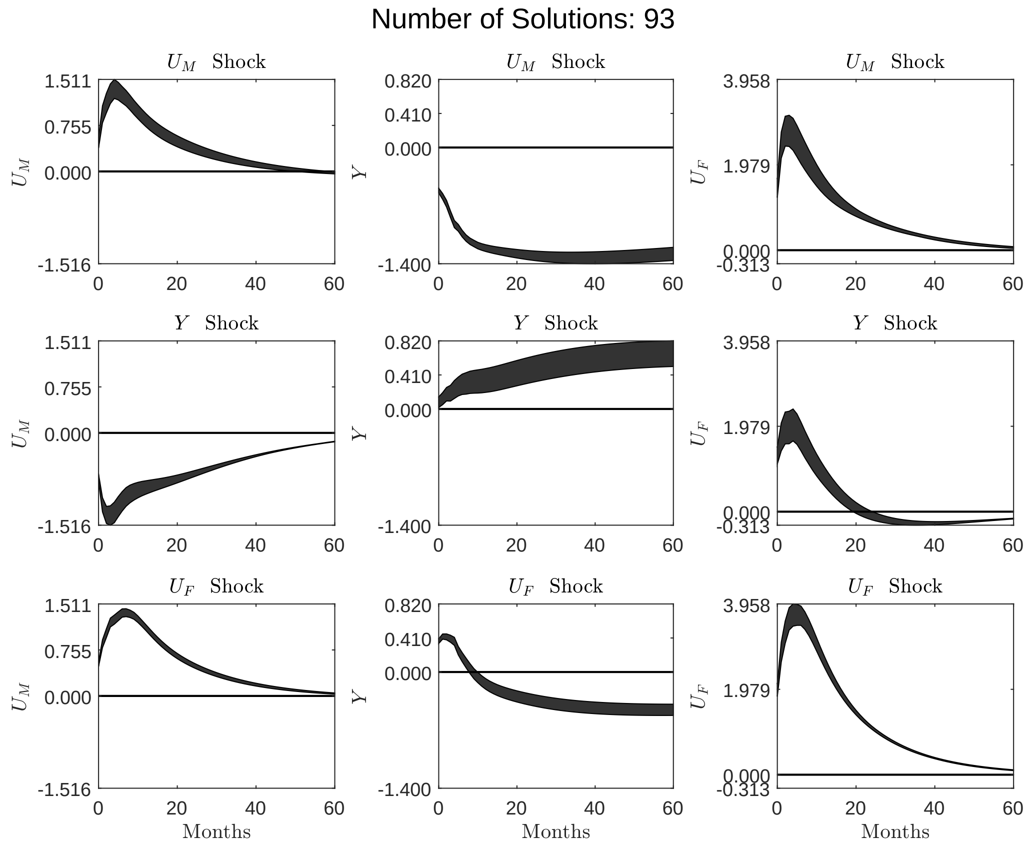


Notes: The figure shows results from the identified set for system $X_t = (U_{Mt}, Y_t, U_{Ft})'$ using the full set of constraints described in (11) with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set adding $\bar{g}_{E7}$ and $\bar{g}_{E8}$ but removing $\bar{g}_{E3}$. The parameters $\bar{k}_5$ and $\bar{k}_6$ are taken to the median value and the $75th$ percentile values of the unconstrained set respectively. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the full set of constraints. The sample spans the period 1960:07 to 2015:04.

also get a persistent negative effect of macroeconomic uncertainty shocks on economic activity (Figure 7). Expanding the sample to 1960:07-2019:12 as previously, we don't find any matrices B satisfying the set of restrictions.

Moreover, examining their macroeconomic uncertainty index, a strong macroeconomic uncertainty shock has been omitted at the beginning of the 1980s which is the second highest peak. It corresponds to the Iran hostages crisis with Operation Eagle Claw in April 1980. However, introducing a restriction on structural macroeconomic uncertainty shocks at this date in all previous applications, we don't find any solutions to compute IRFs showing again that this

Figure 7: Impulse Response Functions modifying $\bar{g}_{E3}$ and adding $\bar{g}_{E7}$, $\bar{g}_{E8}$



Notes: The figure shows results from the identified set for system $X_t = (U_{Mt}, Y_t, U_{Ft})'$ using the full set of constraints described in (11) with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set adding $\bar{g}_{E7}$ and $\bar{g}_{E8}$. The constraint $\bar{g}_{E3}$ is modified by taking $\tau_3 = 1971:08$. The parameters $\bar{k}_5$ and $\bar{k}_6$ are taken to the median values of the unconstrained set. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the full set of constraints. The sample spans the period 1960:07 to 2015:04.

methodology of *event constraints* can be very sensitive.

Summarizing the results of this section, we find that the positive effect of macroeconomic uncertainty shocks on industrial production highlighted by Ludvigson *et al.* (2021) is no longer valid if some new constraints are adding. Our constraints are related to higher uncertainty shocks as the 09/11 attacks and the Russian financial crisis and we also find a negative effect of macroeconomic uncertainty shocks on industrial production. Moreover, by modifying and adding constraints in our applications, either we do not find solutions to compute IRFs or we get a negative effect of macroeconomic uncertainty shocks on economic activity. These findings show that their procedure of identification of structural shocks based on event constraints is very sensitive to the restriction set selected. A careful procedure of robustness checks must be set up if researchers want to apply this novel methodology of *event constraints*.

5 Robustness Checks

In this section, we will assess the robustness of the results in two ways. First, we check to what extent the qualitative results of Ludvigson *et al.* (2021) are modified considering the two months around the one of the $\bar{g}_{E3}$ constraint. Second, we replace the industrial production index with other macroeconomic variables.

5.1 The months around December 1970

The collapse of the Bretton Woods system is hard to relate to a specific month. We have already shown that if we consider 1971:08 instead of 1970:12, the former being a more credible candidate according to us, the positive effect does not old anymore. However, many things may happen in nine months. What if we consider November 1970 or January 1971 instead of December 1970? So we modify the date of the restriction related to Bretton Woods according to Ludvigson *et al.* (2021) taking alternatively these two months instead of December 1970.

We take τ_3 = 1970:11 in the constraint $\bar{g}_{E3}$. As the $75th$ percentile value of e_{Mt} at $t = 1970 : 11$ is negative (-0.42), we need to change slightly the restriction $\bar{g}_{E3}$: $e_{M\tau_3} \geq 0$ at $\tau_3 = 1970 : 11$. This new restriction changes the baseline results of Ludvigson *et al.* (2021). We get a strong negative effect on industrial production (Figure C1). We get similar results taking τ_3 =1971:01 in the constraint $\bar{g}_{E3}$ (Figure C2).[14]

In addition, we have noticed that on December 1970, the number of matrices that respect the $\bar{g}_{E3}$ constraint (given the other constraints) is very weak, 169, compared to 596 on November 1970 (196 for January). The fact that less matrices pass the uncertainty threshold is indicative of a rather not uncertain month compared to the other surrounding month in the subset of matrices

[14]Again, the $75th$ percentile value of e_{Mt} at $t = 1971 : 01$ is also negative (-1.07). Therefore, we modify the restriction as follows: $\bar{g}_{E3} : e_{M\tau_3} \geq 0$ at $\tau_3 = 1971 : 01$.

that satisfy the five other constraints. That is, out of the 1101 matrices that satisfy the five other constraints, most of these exhibit values of macroeconomic uncertainty for the month of December 1970 that do not pass the threshold. Retaining a threshold corresponding to the 75th percentile implies that on average one should retain about 25% of the matrices. However, for this specific month, only 15% of the matrices remain. More, even when lowering the threshold to the 50th percentile (a value of about 1,94), only those 169 matrices remain. And it is still true for a threshold of zero. All this means that the high average level of uncertainty of this month is mainly driven by these 169 matrices since the other matrices that respect the five other constraints exhibit below average uncertainty.

We have already highlighted that the month of December 1970 is an outlier because of the end of the mild recession of 1969-1970 and it now seems that these 169 matrices could be considered as outliers in the outlier. Again, these results show that the choice of 1970:12 is very sensitive and that a rigorous procedure of robustness checks is necessary in the choice of constraints applying the methodology of event constraints.[15] We hope that our work may help improving this promising methodology.

5.2 Examining other macroeconomic variables

We examine the effects of macroeconomic uncertainty shocks on other macroeconomics variables that may be related to growth: consumption and unemployment. The choice of these variables is determined by the availability of data at a monthly frequency.[16] We apply the personal consumption expenditures (C_t) to examine the effects of macroeconomic uncertainty shocks on consumption. Taking the same set of constraints as Ludvigson *et al.* (2021), we get a negative effect of macroeconomic uncertainty shocks on consumption (Figure C3) highlighting that households delay their spending and prefer to save (Leland, 1968).

We repeat the procedure by replacing industrial production with the unemployment rate (U_t). However, in this case, we have to modify the constraint $\bar{g}_{E4}$ on the cumulation of real

[15]The results are qualitatively equivalent applying the real uncertainty index. The results are available upon request

[16]For instance, to the best of our knowledge, there is no variable approximating investment at a monthly frequency.

activity shocks during the Great Recession. Indeed, the cumulation of structural real activity shocks: $\sum_{t=\tau_4} e_{Ut}$ for $\tau_4 \in [2007:12, 2009:06]$ must be positive implying that uncertainty will increase unemployment above its average. Our estimates show that indeed macroeconomic uncertainty shocks have a negative effect on the economy with the rise of unemployment after 6 months (Figure C4): we confirm then that firms delay hiring decisions (Bernanke, 1983; Pindyck, 1991).[17] Overall, all these results confirm our previous ones in that the positive effect of macroeconomic uncertainty shocks on economic activity seems not robust when considering other macroeconomic variables.

6 Conclusion

In recent years, several empirical studies have tried to investigate the impact of uncertainty shocks on macroeconomic variables. The empirical studies of Ludvigson *et al.* (2021) and to a lesser extent that of Larsen (2021) have broken the strong consensus on the negative effect of uncertainty applying an innovative method of identification of structural shocks with *event constraints*. The goal of this paper was to question this striking and controversial conclusion. We find three main shortcomings in Ludvigson *et al.* (2021)'s analysis which prevent to consider their result as robust. Firstly, the choice of the constraint related to Bretton Woods in 1970:12 is questionable. At this date, the level of macroeconomic uncertainty and the level of financial uncertainty do not reach a peak. Furthermore, we have shown in different ways that the positive effect of their macroeconomic uncertainty index on industrial production is linked to this specific constraint only. Removing this restriction, we no longer get their positive effect of macroeconomic uncertainty shocks on industrial production. If we modify this latter constraint by restricting the shock at the date of 1971:08 corresponding to the announcement of the collapse of the Bretton Woods system, we get a negative effect of macroeconomic uncertainty shocks on economic activity. Secondly, we highlight that December 1970 is very specific in that it is the first month following the mild recession of 1969-1970. As a consequence, in this month a catch up has occurred with a strong growth which is by itself a forecast error, a synonym of

[17] The results are qualitatively equivalent applying our constraints on the 09/11 attacks and LTCM.

high uncertainty. Thirdly, if we add new constraints in the model, then we also get the opposite results compared to Ludvigson *et al.* (2021) ones: a negative effect of a macroeconomic uncertainty shock on industrial production is estimated. These findings show that their results are not robust and are very sensitive to slight modifications of the selected constraints. In other words, academics and practitioners should be very careful with the procedure of identification of uncertainty shocks applying this novel methodology of event constraints. Numerous robustness checks must be employed if researchers want to apply their methodology. We hope that our work will contribute to the improvement of this promising method.

Our main conclusion is then that the controversial result of a positive effect of macroeconomic uncertainty on economic activity does not yet seem to be proven. Whether financial or macroeconomic, uncertainty continues to have a negative impact on industrial production. These results are confirmed by several robustness checks. This negative effect of macroeconomic uncertainty that we have estimated in the paper still highlights a wait and see behavior (Bernanke, 1983; Pindyck, 1991) meaning firms delay investment decisions and households delay their consumption and increase their savings.

However, the quest for a positive link between uncertainty and the economic activity related to the growth option theories remains stimulating. Recent high-tech innovations like Artificial Intelligence will provide many growth opportunities for firms and the economy in the future. However, there is uncertainty on the final gains and which firms will benefit from them which will encourage investment, research and development. So, the *growth options* theories refer to a new specific nature of uncertainty which is technological uncertainty. Examining the list of time series included in the macroeconomic uncertainty index, we argue that this list is too large to confirm *growth options* and technological uncertainty. An interesting path to test this assumption could be to develop a new measure of uncertainty related to technology applying big data methodologies.

References

Antolín-Díaz, Juan, & Rubio-Ramírez, Juan F. 2018. Narrative Sign Restrictions for SVARs. *American Economic Review*, **108**(10), 2802–29.

Bachmann, R., Elstner, S., & Sims, E.R. 2013. Uncertainty and Economic Activity: Evidence from Business Survey Data. *American Economic Journal: Macroeconomics*, **5**(2), 217–249.

Baker, S. R., Bloom, N., & Davis, S.J. 2016. Measuring Economic Policy Uncertainty. *Quarterly Journal of Economics*, **131**(4), 1593–1636.

Bernanke, B.S. 1983. Irreversibility, Uncertainty, and Cyclical Investment. *The Quarterly Journal of Economics*, **98**(1), 85–106.

Blanchard, O. 2009. (Nearly) nothing to fear but fear itself. *The Economist*. January 29th.

Bloom, N. 2009. The Impact of Uncertainty Shocks. *Econometrica*, **77**(3), 623–685.

Bloom, N., Kose, M.A., & Terrones, M.E. 2013. Held Back by Uncertainty. *Finance & Development*, **50**(1), 38–41.

Caggiano, Giovanni, Castelnuovo, Efrem, & Pellegrino, Giovanni. 2021. Uncertainty shocks and the great recession: Nonlinearities matter. *Economics Letters*, **198**(C).

Caldara, D., C. Fuentes-Albero, S. Gilchrist, & Zakrajsek, E. 2016. The Macroeconomic Impact of Financial and Uncertainty Shocks. *European Economic Review*, **88**(September), 185–207.

Caldara, Dario, & Iacoviello, Matteo. 2018. *Measuring Geopolitical Risk*. International Finance Discussion Papers 1222. Board of Governors of the Federal Reserve System (U.S.).

Charles, Amélie, Darné, Olivier, & Tripier, Fabien. 2018. Uncertainty and the macroeconomy: evidence from an uncertainty composite indicator. *Applied Economics*, **50**(10), 1093–1107.

Davis, Steven J. 2016 (October). *An Index of Global Economic Policy Uncertainty*. Working Paper 22740. National Bureau of Economic Research.

Dixit, Avinash. 1989. Entry and Exit Decisions under Uncertainty. *Journal of Political Economy*, **97**(3), 620–638.

Gilchrist, Simon, Sim, Jae W, & Zakrajšek, Egon. 2014 (April). *Uncertainty, Financial Frictions, and Investment Dynamics*. Working Paper 20038. National Bureau of Economic Research.

Haddow, Abigail, Hare, Chris, Hooley, John, & Shakir, Tamarah. 2013. *Macroeconomic Uncertainty: What Is It, How Can We Measure It and Why Does It Matter?* Quarterly Bulletin Q2. Bank of England.

Himounet, Nicolas. 2022. Searching the nature of uncertainty: Macroeconomic and financial risks VS geopolitical and pandemic risks. *International Economics*, **170**, 1–31.

Inoue, Atsushi, & Rossi, Barbara. 2021. The Effects of Conventional and Unconventional Monetary Policy: A New Approach. *Quantitative Economics*, **12**(4).

Jurado, Kyle, Ludvigson, Sydney C., & Ng, Serena. 2015. Measuring Uncertainty. *American Economic Review*, **105**(3), 1177–1216.

Larsen, Vegard Høghaug. 2021. Components of Uncertainty. *International Economic Review*, **62**(2), 769–788.

Leduc, Sylvain, & Liu, Zheng. 2016. Uncertainty shocks are aggregate demand shocks. *Journal of Monetary Economics*, **82**, 20 – 35.

Leland, Hayne E. 1968. Saving and Uncertainty: The Precautionary Demand for Saving. *The Quarterly Journal of Economics*, **82**(3), 465–473.

Ludvigson, Sydney C., Ma, Sai, & Ng, Serena. 2021. Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response? *American Economic Journal: Macroeconomics*, **13**(4), 369–410.

Manasse, Paolo, Moramarco, Graziano, & Trigilia, Giulio. 2020. Exchange Rates and Political Uncertainty: The Brexit Case. *SSRN Electronic Journal*, 01.

Oi, Walter Y. 1961. The Desirability of Price Instability Under Perfect Competition. *Econometrica*, **29**(1), 58–64.

Pindyck, Robert S. 1991. Irreversibility, Uncertainty, and Investment. *Journal of Economic Literature*, **29**(3), 1110–1148.

Ramey, Valerie. 2016. Macroeconomic Shocks and Their Propagation. vol. 2. Elsevier.

Rossi, Barbara. 2021. Identifying and estimating the effects of unconventional monetary policy: How to do it and what have we learned? *Econometrics Journal*, **24**(1), 1–32.

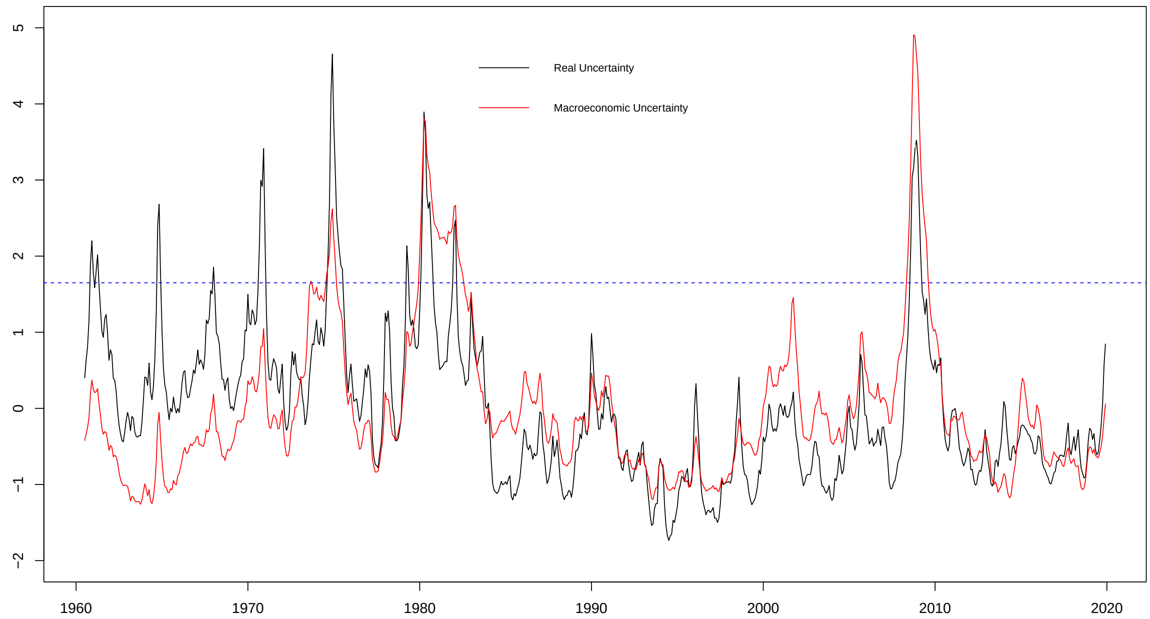
Segal, Gill, Shaliastovich, Ivan, & Yaron, Amir. 2015. Good and bad uncertainty: Macroeconomic and financial market implications. *Journal of Financial Economics*, **117**(2), 369 – 397.

Stock, James H., & Watson, Mark W. 2012 (May). *Disentangling the Channels of the 2007-2009 Recession*. NBER Working Papers 18094. National Bureau of Economic Research, Inc.

Appendix

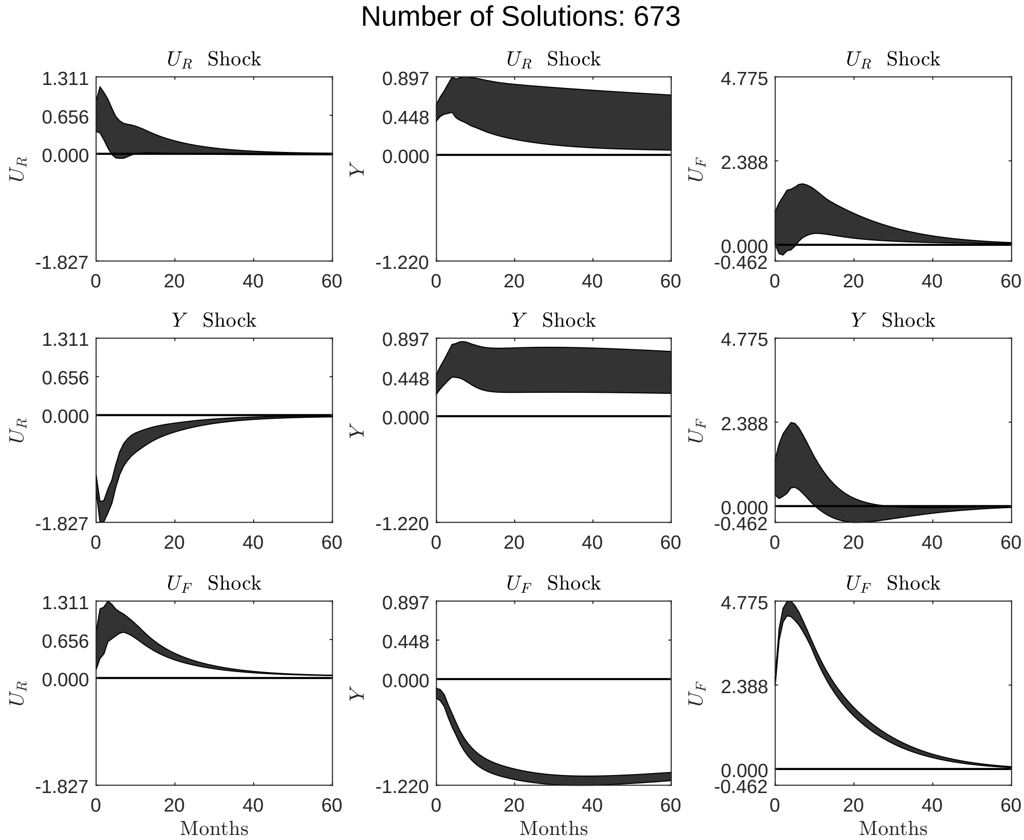
A IRFs using the Real Uncertainty Index

Figure A1: Real Uncertainty Index VS Macroeconomic Uncertainty Index



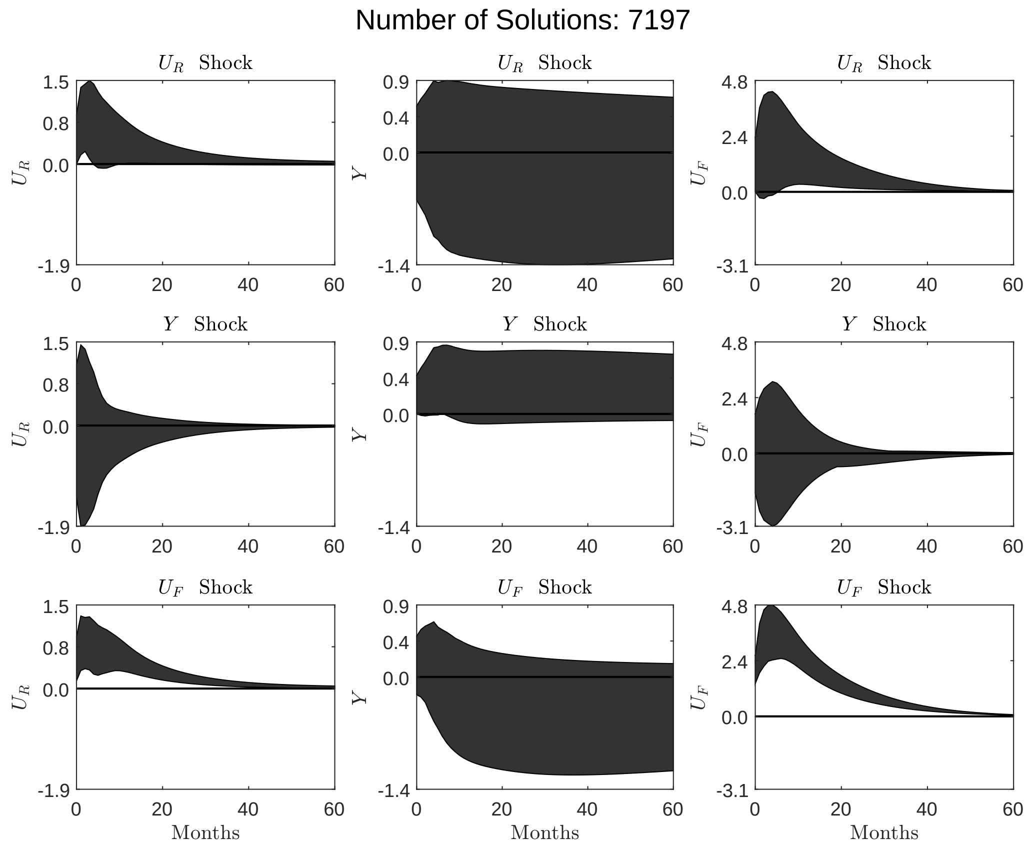
Source: Ludvigson *et al.* (2021)
Notes: The measures are standardized. The horizontal dashed blue line represents the threshold 1.65. The solid red line corresponds to the macroeconomic uncertainty index of Ludvigson *et al.* (2021). The solid black line corresponds to the real uncertainty index of Ludvigson *et al.* (2021).

Figure A2: Impulse Response Functions of Ludvigson *et al.* (2021)



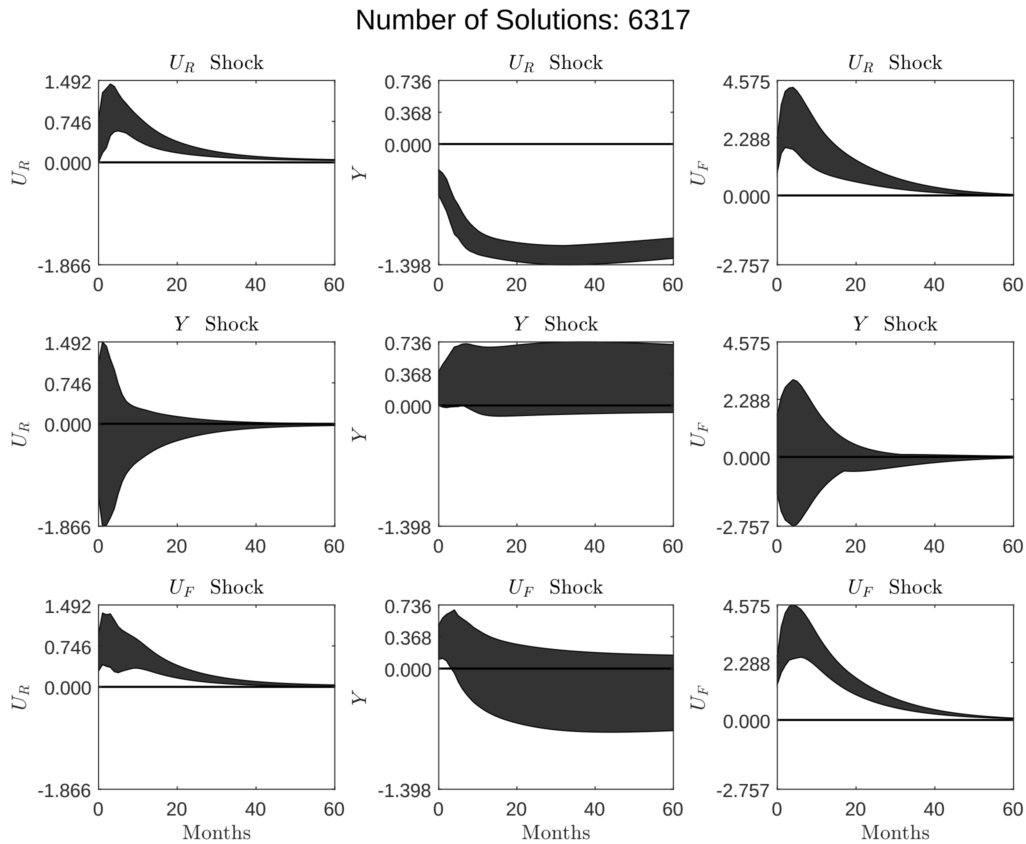
Notes: The figure shows results from the identified set for the system $X_t = (U_{Rt}, Y_t, U_{Ft})'$ using the full set of constraints described in (11) with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the full set of constraints described in (11). The sample spans the period 1960:07 to 2015:04.

Figure A3: Impulse Response Functions removing $\bar{g}_{E3}$



Notes: The figure shows results from the identified set for the system $X_t = (U_{Rt}, Y_t, U_{Ft})'$ using the set of constraints described in (11) but removing $\bar{g}_{E3}$ with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the set of retained constraints. The sample spans the period 1960:07 to 2015:04.

Figure A4: Impulse Response Functions modifying $\bar{g}_{E3}$



Notes: The figure shows results from the identified set for the system $X_t = (U_{Rt}, Y_t, U_{Ft})'$ using the set of constraints described in (11) but modifying $\bar{g}_{E3}$ with $\tau_3 = 1971:08$. Each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the set of retained constraints. The sample spans the period 1960:07 to 2015:04.

B Disaggregating the Real Uncertainty Index

This appendix aims at explaining why the real uncertainty index exhibits a peak on 1970:12. To compute their real uncertainty index, Ludvigson *et al.* (2021) aggregated uncertainty related to 73 time series among the 132 times series applied to get their baseline macroeconomic uncertainty index (Figure A1). These 73 time series are related to the first four groups of the McCracken database corresponding to real activity : output and income, labor market, housing (constructions) and a group related to consumption, orders and inventories.[18]

The goal is to decompose the real uncertainty index to investigate which variables can explain the peak on 1970:12. To achieve it, we must reproduce the real uncertainty of Ludvigson *et al.* (2021) over the period 1960:07 to 2019:12 to extract its components as the data of these 73 uncertainty indexes are not available for this sample.[19] We research for all variables exhibiting a spike on 1970:12. A high peak is detected on 1970:12 for uncertainty related to industrial production (Figure B1). Other indexes related to industrial production within the first group also reach a strong peak at this date: namely final products and non industrial supplies, final products-market group, consumer goods, durable consumer goods, non durable consumer goods, business equipment, materials, durable materials, manufacturing. These findings show that the variables related to production are a source of the peak of real uncertainty.[20] The measure related to employment (manufacturing) exhibits a spike in 1970:12 (Figure B2). The same peak is detected for other measures of employment: total nonfarm, durable goods, construction, goods-producing industries, average hourly earnings-manufacturing, civilians unemployed

[18]A detailed list of the time series is available on the McCracken website.

[19]To get their index, Ludvigson *et al.* (2021) also applied a set of 147 financial variables in their econometric methodology. Unfortunately, these financial data are not available. However, we were able to reproduce their real uncertainty index without these financial data with a correlation close to 0.995. The correlation is statistically significant with a p-value close to 0. The results are available upon request.

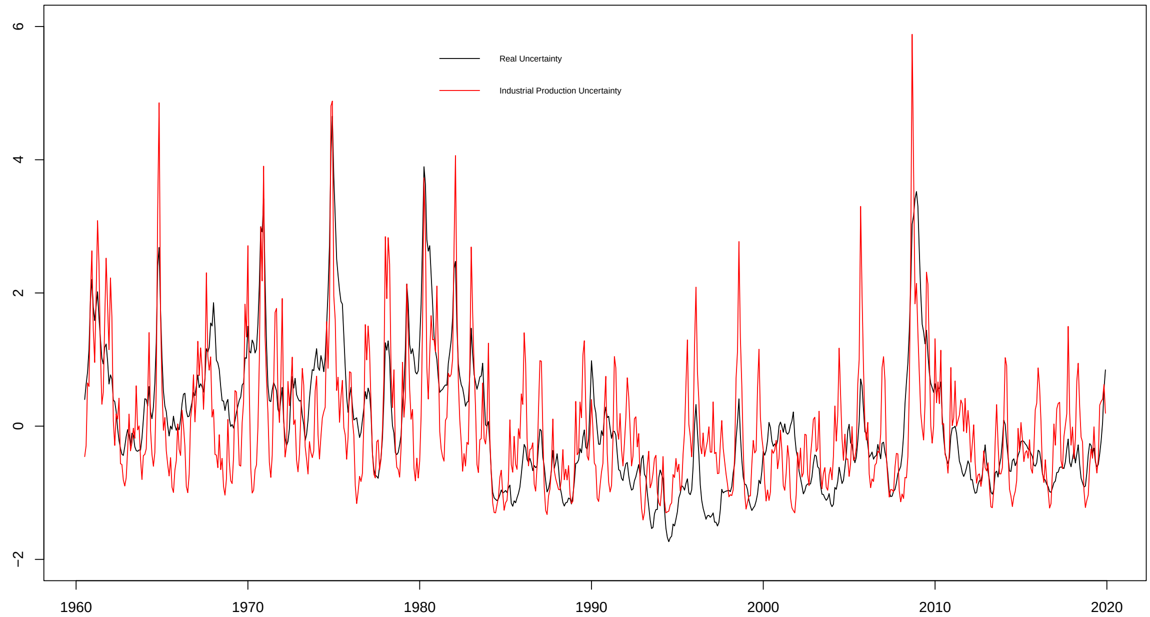
[20]The results are available upon request.

for 5-14 weeks, civilians unemployed - 15 weeks & over.... The strong uncertainty peak on 1970:12 is not detected for the variables related to housing (third group), consumption, orders and inventories (fourth group).[21] These results show that the high uncertainty peak detected on 1970:12 is mainly generated by variables related to production and employment.

When looking at the different variables that enter the real uncertainty index of Ludvigson *et al.* (2021), we observe a surge of growth in this specific month of December 1970 which is a catch up after the mild recession of 1969-1970. Hence, just keeping uncertainty peaks for this specific month may artificially associate a high uncertainty to a very specific episode of strong growth. This may explain the positive sign found with the constraint on December 1970. Moreover, we shall remind that the uncertainty measure of Ludvigson *et al.* (2021) is based on the residuals of econometric specifications, that is the part that is unexplained by the model estimated. As a matter of fact, since the 1969-1970 recession has lasted 11 months, from December 1969 to November 1970, the most probable forecast for the following month was another month of recession which is not what happened. So the strong catch up in growth of December 1970 also constitutes an important forecast error. Therefore, the strong growth and strong uncertainty indeed appeared in December 1970.

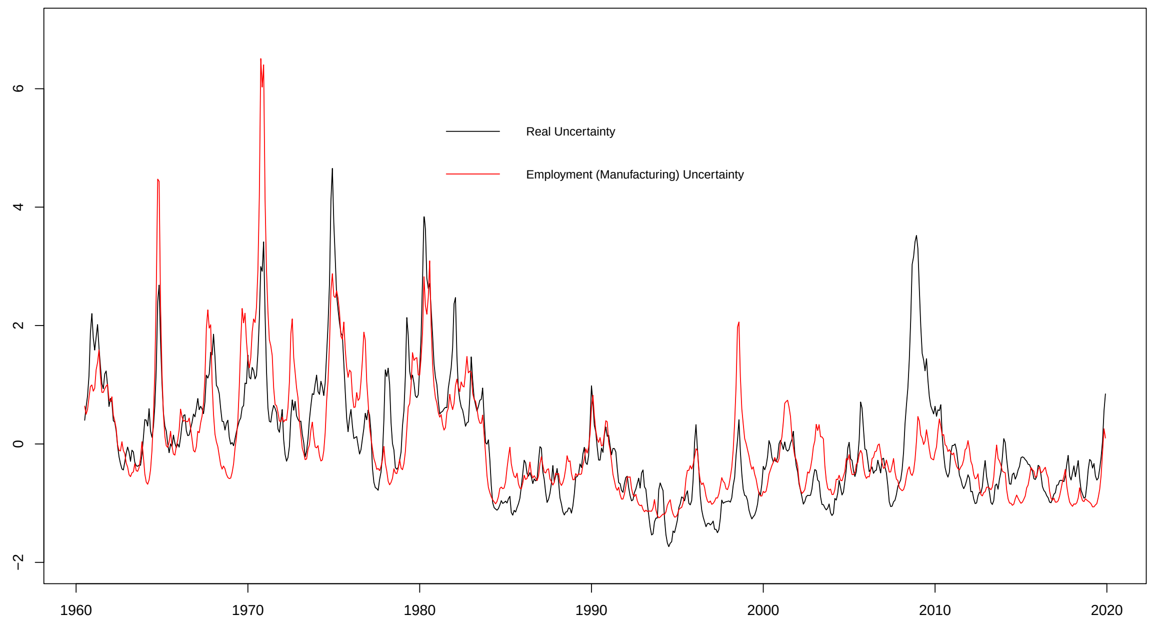
[21]Figure B3 plots uncertainty related to housing starts to illustrate this point on 1970:12.

Figure B1: Real Uncertainty Index VS Industrial Production Uncertainty



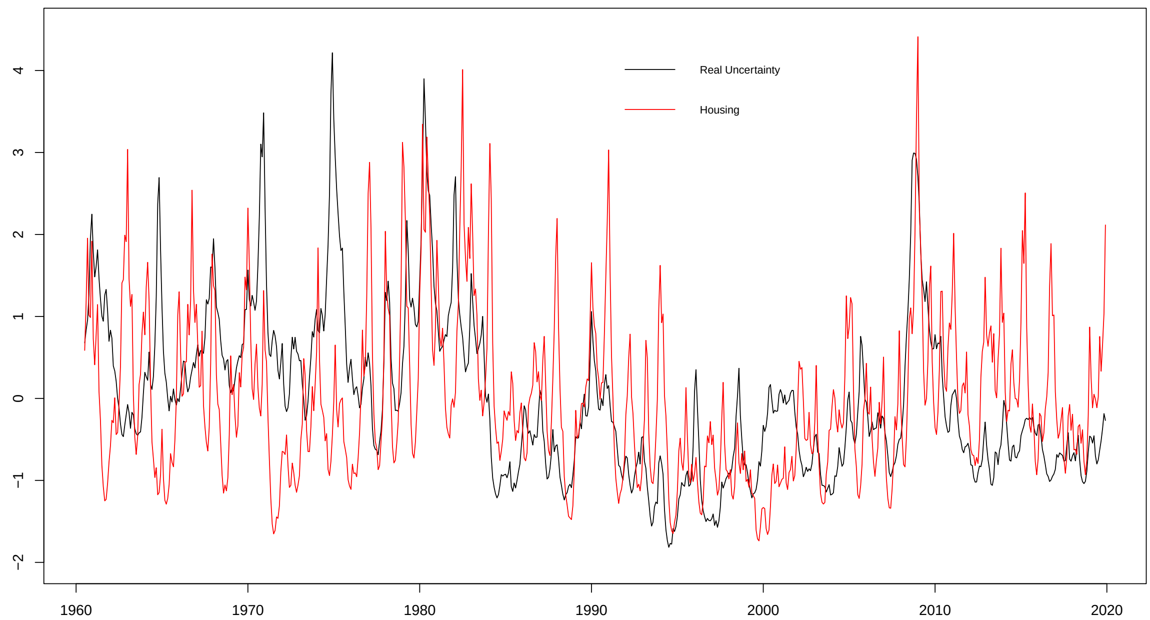
Notes: The measures are standardized. The horizontal dashed blue line represents the threshold 1.65. The solid red line corresponds to an uncertainty index related to industrial computed from the Ludvigson *et al.* (2021)'s framework. The solid black line corresponds to the real uncertainty index of Ludvigson *et al.* (2021).

Figure B2: Real Uncertainty Index VS Employment Uncertainty



Notes: The measures are standardized. The horizontal dashed blue line represents the threshold 1.65. The solid red line corresponds to an uncertainty index related to employment computed from the Ludvigson *et al.* (2021)'s framework. The solid black line corresponds to the real uncertainty index of Ludvigson *et al.* (2021).

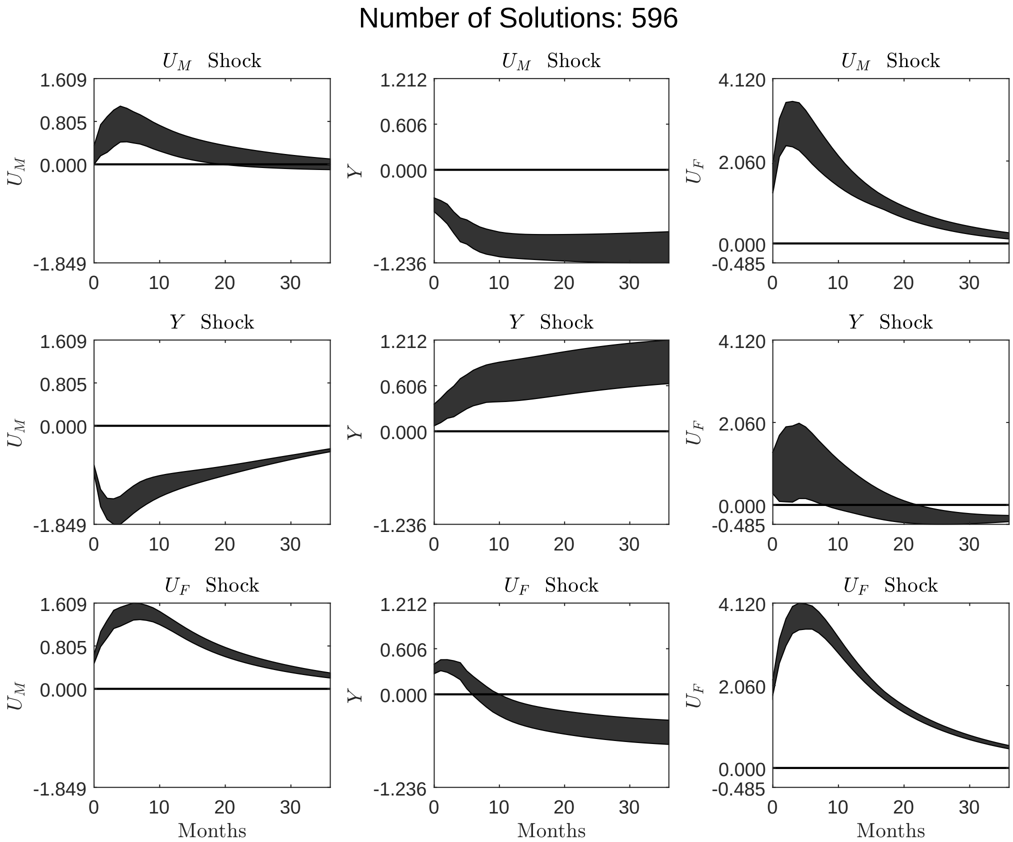
Figure B3: Real Uncertainty Index VS Housing Uncertainty



Notes: The measures are standardized. The horizontal dashed blue line represents the threshold 1.65. The solid red line corresponds to an uncertainty index related to housing starts computed from the Ludvigson *et al.* (2021)'s framework. The solid black line corresponds to the real uncertainty index of Ludvigson *et al.* (2021).

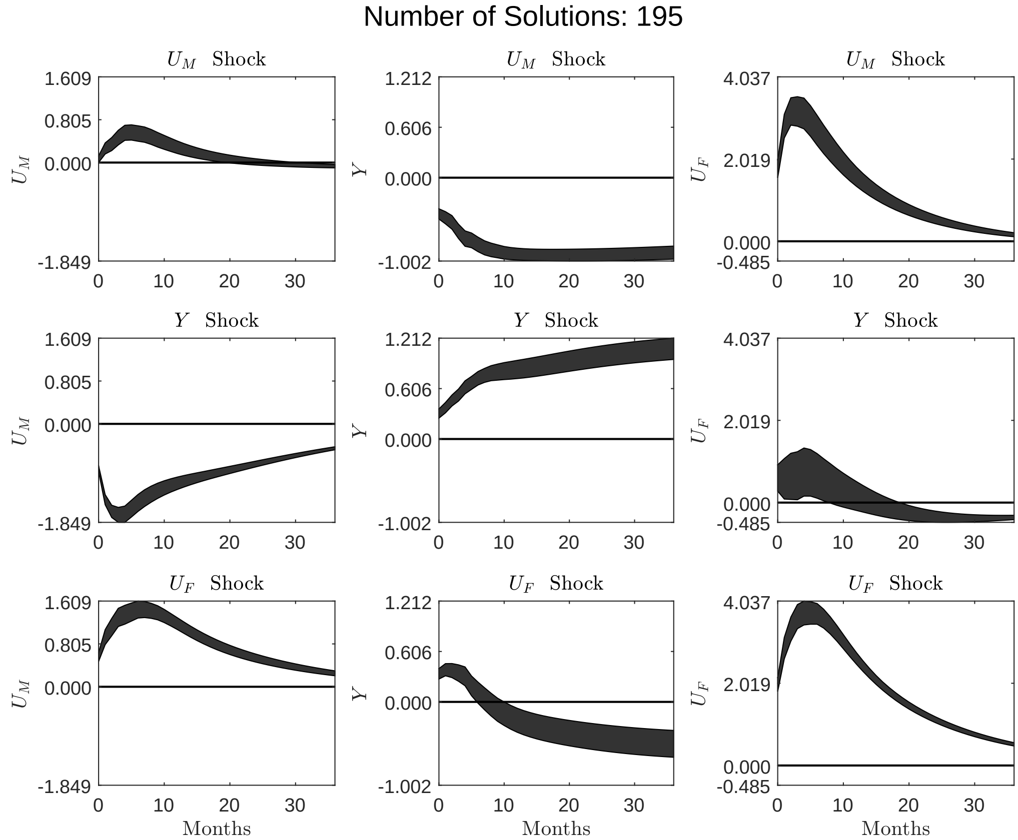
C Robustness Checks

Figure C1: Impulse Response Functions modifying the constraint $\bar{g}_{E3}$ (τ_3 =1970:11)



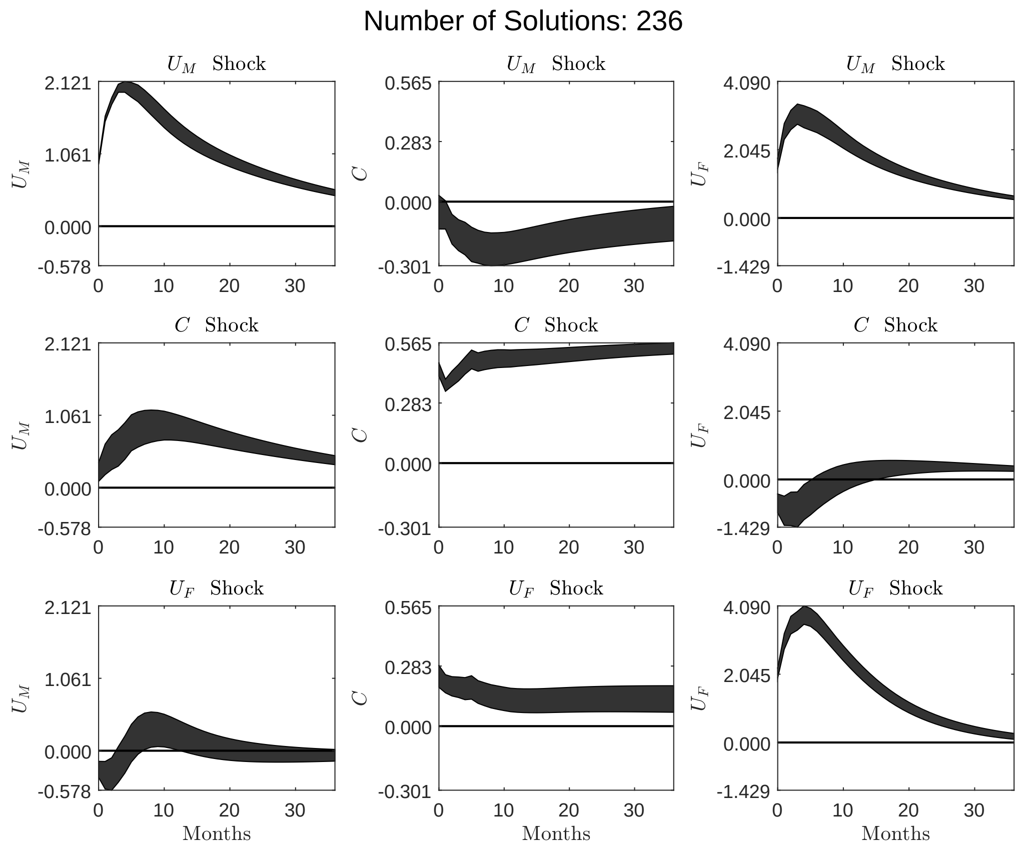
Notes: The figure shows results from the identified set for the system $X_t = (U_{Mt}, Y_t, U_{Ft})'$ using the set of constraints. We modify the constraint $\bar{g}_{E3}$ as follows: $\bar{g}_{E3} : e_{M\tau_3} \geq 0$ at $\tau_3 = 1970 : 11$. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the set of constraints. The sample spans the period 1960:07 to 2015:04.

Figure C2: Impulse Response Functions modifying the constraint $\bar{g}_{E3}$ (τ_3 =1971:01)



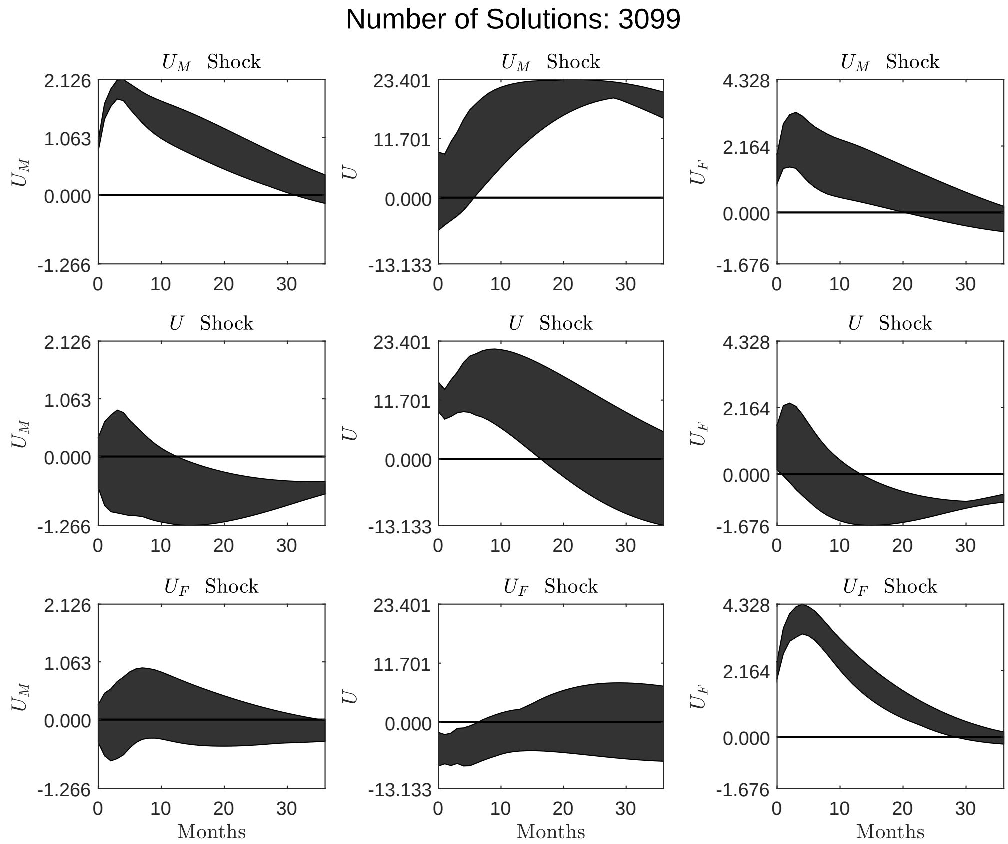
Notes: The figure shows results from the identified set for the system $X_t = (U_{Mt}, Y_t, U_{Ft})'$ using the set of constraints. We modify the constraint $\bar{g}_{E3}$ as follows: $\bar{g}_{E3} : e_{M\tau_3} \geq 0$ at $\tau_3 = 1971:01$. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the set of constraints. The sample spans the period 1960:07 to 2015:04.

Figure C3: Impulse Response Functions applying the personal consumption expenditures (C_t)



Notes: The figure shows results from the identified set for the system $X_t = (U_{Mt}, C_t, U_{Ft})'$ using the set of constraints with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the set of constraints. The sample spans the period 1960:07 to 2015:04.

Figure C4: Impulse Response Functions applying the unemployment rate (U_t)



Notes: The figure shows results from the identified set for the system $X_t = (U_{Mt}, U_t, U_{Ft})'$ using the set of constraints with each argument of $\bar{k}$ set to their 75th-percentile values of the unconstrained set. The constraint $\bar{g}_{E4}$ is modified as follows: $\sum_{t=\tau_4} e_{Ut} \geq 0$ for $\tau_4 \in [2007:12, 2009:06]$. The solid lines report the identified set of impulse response functions. The number of solutions indicates how many matrices B satisfy the set of constraints. The sample spans the period 1960:07 to 2015:04.