On the Identification of Financial and Uncertainty Shocks☆

Dario Caldara[a], Cristina Fuentes-Albero[b], Simon Gilchrist[c], Egon Zakrajšek[a]

[a] *Board of Governors of the Federal Reserve System*

[b] *Department of Economics, Rutgers University*

[c] *Department of Economics, Boston University*

Abstract

There is a consensus about the increasing exposure to disruptions in the financial system and economic uncertainty over the recent years. Despite their different implications for policy, discriminating empirically between these two sources of economic fluctuations is not an easy task because their available empirical proxies are strongly correlated. We aim at making progress in discriminating financial and uncertainty shocks by means of an atheoretical approach to identification following the penalty function proposed by Uhlig (2003). We conclude that while the uncertainty channel plays a negligible role in the transmission of financial shocks; the financial channel is key in the transmission of uncertainty shocks. Financial shocks generate slowly-building and economically significant recessions followed by slow recoveries. Uncertainty shocks generate similar adverse effects if transmitted through the financial channel; otherwise, they have significantly smaller effects in economic activity.

JEL CLASSIFICATION: E32, E37, E44

Keywords: Financial shocks, uncertainty shocks, penalty function, identification

☆The views expressed herein are those of the authors and not necessarily those of the Board of Governors or the Federal Reserve System.

Email addresses: `Dario.Caldara@frb.gov` (Dario Caldara), `cfuentes@econ.rutgers.edu` (Cristina Fuentes-Albero), `sgilchri@bu.edu` (Simon Gilchrist), `egon.zakrajsek@frb.gov` (Egon Zakrajšek)

1. Introduction

The 2007-2009 recession has casted some doubt on the relative importance of standard drivers of U.S. business cycles. Researchers have highlighted two alternative drivers of fluctuations: financial market disruptions and economic uncertainty. While there is a consensus among researchers and practitioners on the 2007-2009 recession being originated by financial market disruptions, there is no agreement on whether the subsequent slow recovery is due to financial factors or to the increasing uncertainty about fiscal, monetary, and regulatory policy. Stock and Watson (2012) find a large correlation between measures of financial distress and uncertainty proxies so they conclude that these variables account for similar features of the data. But the policy implications of financial and uncertainty shocks are quite different, which requires advances in discriminating empirically between these two sources of economic fluctuations. In this paper, we aim at making progress in this direction by means of a statistical approach to identification.

We propose to identify financial and uncertainty shocks by means of two-step strategies based on the penalty function approach proposed by Faust (1998) and extended by Uhlig (2003). In a nutshell, the penalty function approach to identification consists of searching for innovations that account for the maximal amount of the forecast error variance of a target variable in a given time horizon. We consider two identification strategies. On the one hand, we search for the largest shock accounting for the maximal amount of the forecast error variance (FEV, thereafter) of a credit spread, adjusted to eliminate predictable default risk as in Gilchrist and Zakrajšek (2012), over a three-month horizon. We label the extracted shock as a *financial shock*. Conditional on this shock, we search for the largest shock explaining the largest share of the FEV of an uncertainty proxy over a three-month horizon. Under this identification strategy, the uncertainty shock is essentially a remainder so we refer to it as a *non-financial uncertainty shock*. On the other hand, we revert the order in the identification strategy so we first search for the largest shock accounting for the maximal amount of the FEV of the uncertainty proxy over a three-month horizon and label this shock as *uncertainty shock*. Conditional on the uncertainty shock, we search for the shock explaining the largest amount of the FEV of the credit spread in the three months after impact. We label this shock as *non-uncertainty related financial shock*. The first identification strategy makes it hard for uncertainty shocks to matter, but it extracts the most powerful financial shock in the system. The second strategy delivers the most powerful uncertainty shock by minimizing the role played by financial shocks.

We conclude that conditions in financial markets for the corporate sector are a key element in the transmission mechanism of fluctuations in economic uncertainty. That is, while *uncertainty shocks* generate economically significant recessions, *non-financial uncertainty shocks* play a smaller role as drivers of aggregate economic fluctuations. However, fluctuations in financial rigidities are a relevant driver of economic activity under both identification schemes. In particular, adverse financial shocks generate a slowly building sizable recession that bottoms out about 24 months after the shock to start a very slow recovery. Thus, the uncertainty channel does not play a significant role in the transmission of financial shocks.

In order to test the ultimate role played by the financial channel in the transmission of uncertainty shocks, we perform the following exercise. We identify the largest shock accounting for the maximal amount of the FEV of the uncertainty proxy over a three-month horizon and generating a zero response upon impact on the excess bond premium (the credit spread adjusted for expected default risk). The large reduction in the size of the adverse economic effects strengthens the result on the key role played by the financial channel in the transmission of fluctuations in economic uncertainty. We perform the same exercise for financial shocks, that is, we impose a zero response upon impact on uncertainty. The responses are fairly similar to the ones obtained under the two-step identification strategies, which corroborates our statement on the uncertainty channel being not too relevant in the transmission of financial shocks.

Finally, we assess the relative importance of the shocks identified in driving aggregate fluctuations by means of the FEV. We conclude that *financial shocks* account for 25-30% of the FEV for real variables and 5-10% of the FEV for nominal variables at the two-year horizon. If we condition on the uncertainty shocks, the relative importance of financial shocks for nominal variables does not change and the one for real variables drops to 20% of the FEV. Uncertainty related shocks account for at most 5% of the FEV for nominal variables. Regarding their relative importance for real variables, *uncertainty shocks* account for 5 % of the FEV for real variables; but *non-financial uncertainty shocks* explain almost nothing of such FEV. Therefore, we conclude that irrespective of the labeling, the driving force of the excess bond premium has enough informative content so as to be an important driver of U.S. economic activity, while dispersion measures are not able to play such a relevant role by themselves.

The literature on analyzing financial crisis using macro and financial data is large, but mostly focused on determining whether financial crisis are predictable. However, Donaldson (1992), Canova (1994) and, more recently, Nason and Tallman (2012) take on analyzing whether the factors driving non-crisis business cycle fluctuations also drive crisis. Nason and Tallman (2012) estimate Markov-switching VAR models on an annual data set from 1890 to 2010. They identify credit supply shocks with shocks to inside money and credit demand shocks with shocks to the short-term interest rate. Most of the recent contributions to the literature do not differentiate between regimes (crisis versus non-crisis) and have focused on identifying financial shocks using either recursive orderings or sign restrictions. Gilchrist and Zakrajšek (2012) identify financial shocks using recursive orderings. They place their proxy for financial rigidities, the excess bond premium, after the real block and inflation but before risk-free interest rates and stock market returns. Financial shocks account for 25% of the forecast error variance of investment but only 10% of that of output, consumption, prices, and risk-free rates. Meeks (2012) estimates a VAR model on monthly data including expected default rates and a high yield bond spread for a portfolio with quality rating in the B1/B2 range. He assumes that adverse financial shocks increase both expected default rates and the credit spread but the relative magnitude of the increase in the latter should exceed the increase in default rates. He concludes that the identified financial shocks are not too relevant as drivers of aggregate fluctuations. Moreover, financial shocks account only for 15% of the forecast error variance of credit spreads. Gambetti and Musso (2012) use sign restrictions to identify credit supply shocks and conclude that these shocks account for about 20% of the variation in real GDP, inflation and loans but only 10% of the variance of lending rate and the short term interest rate. Thus, there is a wide range of results regarding the relative importance of financial shocks as drivers of the U.S. business cycle.

The interest on the role played by uncertainty shocks has increased since the seminal paper by Bloom (2009). He identifies uncertainty shocks using recursive orderings by placing the uncertainty proxy, a stock market volatility index, after stock market returns but before the real and nominal block. He concludes that uncertainty shocks have a negligible response upon impact for real variables followed by a rapid drop and rebound. Thus, uncertainty shocks have lagged recessionary effects that are short-lasting. Baker et al. (2012) proceed by placing the policy uncertainty index first in the VAR and conclude that uncertainty shocks are followed by persistent and significantly large declines in real variables. Bachmann et al. (2012) use a survey-based disagreement measure to proxy for uncertainty. They also conclude that uncertainty shocks generates initially small effects but the recessionary effects are slowly building and almost permanent. Their uncertainty shocks account for up to 20% of the forecast error variance of output at the five-year horizon. Therefore, depending on the proxy used and the ordering in the Cholesky decomposition, the transmission of uncertainty shocks is different.

Popescu and Smets (2010) identify both financial and uncertainty shocks for the German economy using recursive orderings. They place the uncertainty proxy after the macro block but before the the financial market risk index. They conclude that uncertainty shocks have small and temporary effects on output and financial risk premia. Moreover, the contribution of uncertainty shocks to the forecast error variance of these two variables is very small, of about 3%. The effects of financial variables are more long-lasting and account for up to 15% of the variation in output. Gilchrist et al. (2012) also consider both financial and uncertainty shocks and proceed to identify them using recursive orderings. They conclude that the ordering of the uncertainty proxy and the credit spread for triple-B bonds matter for the transmission of uncertainty shocks.

The remainder of the paper is organized as follows. We introduce the data used in the paper and discuss some preliminary analysis of the data base in Section 2. The econometric model and the identification strategies are described in Section 3. Section 4 presents the results of the paper and Section 5 provides a robustness analysis. Section 6 concludes.

2. Empirical analysis

2.1. Data sources

We estimate eight-variate vector autoregressive models of order six on monthly data sets containing a real block, a nominal block, a measure of stock market returns, an uncertainty proxy, and a proxy for financial distress. The real block has two components: the log of the real counterpart of the industrial production index provided by the Board of Governors and the log of employment (in thousands) in the nonfarm business sector provided by the Bureau of Labor Statistics (BLS). In the nominal block, we include the log of the consumer price index (CPI) provided by the BLS, the effective federal funds rate, and the 10-year Treasury constant maturity rate.

We consider daily firm-level stock returns to construct our benchmark estimate of time-varying economic uncertainty and the measure of stock market returns to be included in the VAR model. From the Center for Research in Security Prices (CRSP), we extract daily stock returns for all U.S. nonfinancial corporations with at least 1,250 trading days over the period from January, 1970 to December, 2011.

Our measure of stock returns in the VAR model is the monthly cross-sectional average. The benchmark estimate for economic uncertainty the so-called realized volatility (RVOL), which is a statistical measure of the variability of returns relative to an average price return. The monthly realized volatility of the measure of stock market returns in our data set is calculated using a standardized formula that uses continuously compounded daily returns over a month assuming a mean daily price return of zero and is annualized assuming 252 trading days per year. In particular, we consider the following formula when calculating realized volatility:

$$RVOL = 100\sqrt{\frac{252}{n}\sum_{t=1}^{n} R_t^2} \tag{1}$$

where n is the number of trading days in the measurement time frame.

We also explore alternative proxies for economic uncertainty put forward by other researchers: a monthly version of the idiosyncratic volatility measure proposed by Gilchrist et al. (2012), the survey disagreement measure constructed by Bachmann et al. (2012), the Chicago Board of Option Exchange VXO index of percentage implied volatility proposed by Bloom (2009), the Google news index constructed by Baker et al. (2012), and the economic uncertainty policy index also put forward by Baker et al. (2012). The Google news based economic uncertainty index is defined as the ratio of the number of articles in a given month containing the word uncertainty or phrases related with the economy to the number of articles containing the word today to account for the increasing volume of news. The economic uncertainty policy index (BBD hereafter) is constructed from the following underlying components: the frequency of newspaper references to economic policy uncertainty, the number of federal tax code provisions set to expire in future year, and the extent of forecaster disagreement over future inflation and government purchases. The measure of idiosyncratic volatility and the forecast disagreement measure are available from 1973, the implied volatility from 1986, and the two indexes constructed by Baker et al. (2012) from 1985. We report the summary statistics for these alternative proxies for uncertainty in Table 1.

Table 1: Summary statistics

	Mean	St Dev	Min	P50	Max	Autocor
EBP	0.04	0.58	-1.33	-0.07	2.97	0.88
RVOL	14.81	9.77	4.04	11.79	80.97	0.71
IVOL	50.53	14.37	12.74	49.24	119.48	0.58
DISP	0.71	0.06	0.51	0.70	0.84	0.69
Google	100.00	63.75	28.28	84.54	437.60	0.90
BBD	104.71	31.02	57.22	97.88	244.82	0.83
VXO	21.49	8.54	9.82	20.18	61.41	0.83

Notes: The sample ranges from 1985:M1 to 2011:M12 for all variables but VXO for which the sample starts in 1986:M1.

Gilchrist et al. (2012) use the same daily firm level data we propose above to construct a quarterly measure of time-varying idiosyncratic uncertainty. We replicate their strategy to construct a monthly measure of idiosyncratic volatility (IVOL). In a first step, we remove the systematic component of daily equity returns using a four-factor model. In particular, we augment the standard Fama and French (1992) three-factor model with the momentum risk factor proposed by Carhart (1997). Let u_{it_d} be the OLS residual from the four-factor model, that is, $\widehat{u}_{it_d}$ is the idiosyncratic return and let $\bar{u}_{it_d}$ be the sample mean of daily idiosyncratic returns in month t. We can compute a measure for firm-level time-varying equity volatility as follows

$$\sigma_{it} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\widehat{u}_{it_d} - \bar{u}_{it_d}\right)^2} \tag{2}$$

Let us assume that this monthly estimate of idiosyncratic volatility follows an autoregressive process of the following form

$$\log\sigma_{it} = \gamma_i + \delta_i t + \rho\log\sigma_{it-1} + \nu_t + \epsilon_{it},\ \ \epsilon_{it} \sim \mathcal{N}\left(0, \varphi^2\right) \tag{3}$$

where γ_i stands for firm fixed effects, which controls for the cross-sectional heterogeneity of σ_{it} and ν_t is a sequence of time fixed effects, which captures shocks to idiosyncratic volatility that are common to all firms. These time fixed effects constitute our estimate for economic uncertainty labeled as idiosyncratic volatility (IVOL).

Bachmann et al. (2012) use forecast disagreement from the Business Outlook Survey administered by the Federal Reserve Bank of Philadelphia to construct an empirical proxy for time-varying business-level uncertainty. The survey comprises large manufacturing firms in the Third Fed district: Delaware, the southern half of New Jersey, and the eastern two-thirds of Pennsylvania. The sample size for each month is about 100-125 firms. Bachmann et al. (2012) focus on the answers to the following two questions in the survey: *Q3: General business conditions: What is your evaluation of the level of general business activity six months from now vs. [current month]: decrease, no change, increase?* and *Q4: Company business indicators: Shipments six months from now vs. [current month]: decrease, no change, increase?*. The answers are coded into the following categories: decrease (-1), no change (0), and increase (+1). Let $Frac_t^+$ be the fraction of firms in the cross-section with "increase" responses at time t and $Frac_t^-$ be the fraction with "decrease" responses. The uncertainty proxy (DISP) is given by the following relative score

$$DISP_t = \sqrt{Frac_t^+ + Frac_t^- - \left(Frac_t^+ - Frac_t^-\right)^2} \tag{4}$$

Researchers and practitioners have traditionally used credit spreads to proxy for financial distress, but credit spreads are subject to the standard duration mismatch. Gilchrist and Zakrajšek (2012) construct a duration mismatch free credit spread index with high information content for future economic activity using micro-level data. Let $S_{it}[k]$ be the spread of the yield of bond k issued by firm i over the yield of a synthetic risk-free security with identical cash-flows. Then the GZ credit spread is defined as the arithmetic average of credit spreads on outstanding bonds in a given month

$$S_t^{GZ} = \frac{1}{N_t} \sum_i \sum_k S_{it}[k] \tag{5}$$

where N_t is the number of observations in month t.

Gilchrist and Zakrajšek (2012) use month-end secondary market prices of outstanding securities from the Lehman/Warga and Merrill Lynch databases for a sample of U.S. nonfinancial firms covered by S&P's Compustat and CRSP. They focus only on senior unsecured issues with a fixed schedule. To avoid a large influence of extreme observations, they use the following criteria to eliminate observations from the data set. Observations with credit spreads below 5 basis points and greater than 3,500 basis points are eliminated. They also remove small corporate issues (par value of less than $1 million) and observations with term to maturity of less than 1 year or more than 30 years. The definitive database contains 5,982 individual securities corresponding to 1,112 firms. The database comprises the entire spectrum of credit quality, ranging from single D to triple A (S&P credit ratings).

The GZ index can be decomposed into two components: a component capturing systematic movements in default risk of firms and a residual component capturing the variation in the average price of bearing exposure to corporate risk beyond the compensation for expected default. This residual component, labeled as the excess bond premium (EBP), is our benchmark proxy for financial distress.

Let DFT_{it} be a firm-specific measure of expected default constructed using the distance to default framework proposed by Merton (1974)[1] and let $Z_{it}[k]$ be a vector of bond-specific characteristics[2]. Then, the log of the credit spread on bond k (issued by firm i) is assumed to be linearly related to DFT_{it} and $Z_{it}[k]$ as follows

$$\log S_{it}[k] = \beta DFT_{it} + \gamma' Z_{it}[k] + \epsilon_{it}[k] \tag{6}$$

[1] For a detailed description of the computation of this firm-specific measure of default risk, we refer the reader to Gilchrist and Zakrajšek (2012).

[2] The vector of bond-specific characteristics include the bond's duration, the amount outstanding, the (fixed) coupon rate, the age of the issue, and an indicator variable that is equal to 1 if the bond is callable and zero otherwise.

Under Gaussian innovations, the predicted level of the spread on bond k is given by

$$\widehat{S}_{it}[k] = \exp\left[\widehat{\beta} DFT_{it} + \widehat{\gamma}' Z_{it}[k] + \frac{\widehat{\sigma}^2}{2}\right] \tag{7}$$

Thus, we have that the predicted component of the GZ credit spread at time t is defined as

$$\widehat{S}_t^{GZ} = \frac{1}{N_t} \sum_i \sum_k \widehat{S}_{it}[k] \tag{8}$$

We can define the excess bond premium as the unpredicted component of the GZ spread

$$EBP_t = S_t^{GZ} - \widehat{S}_t^{GZ} \tag{9}$$

Figure 1 reports the time series for the uncertainty measures and the proxy for financial distress considered in the paper joint with the NBER dated recessions in the US economy.

2.2. Granger causality analysis

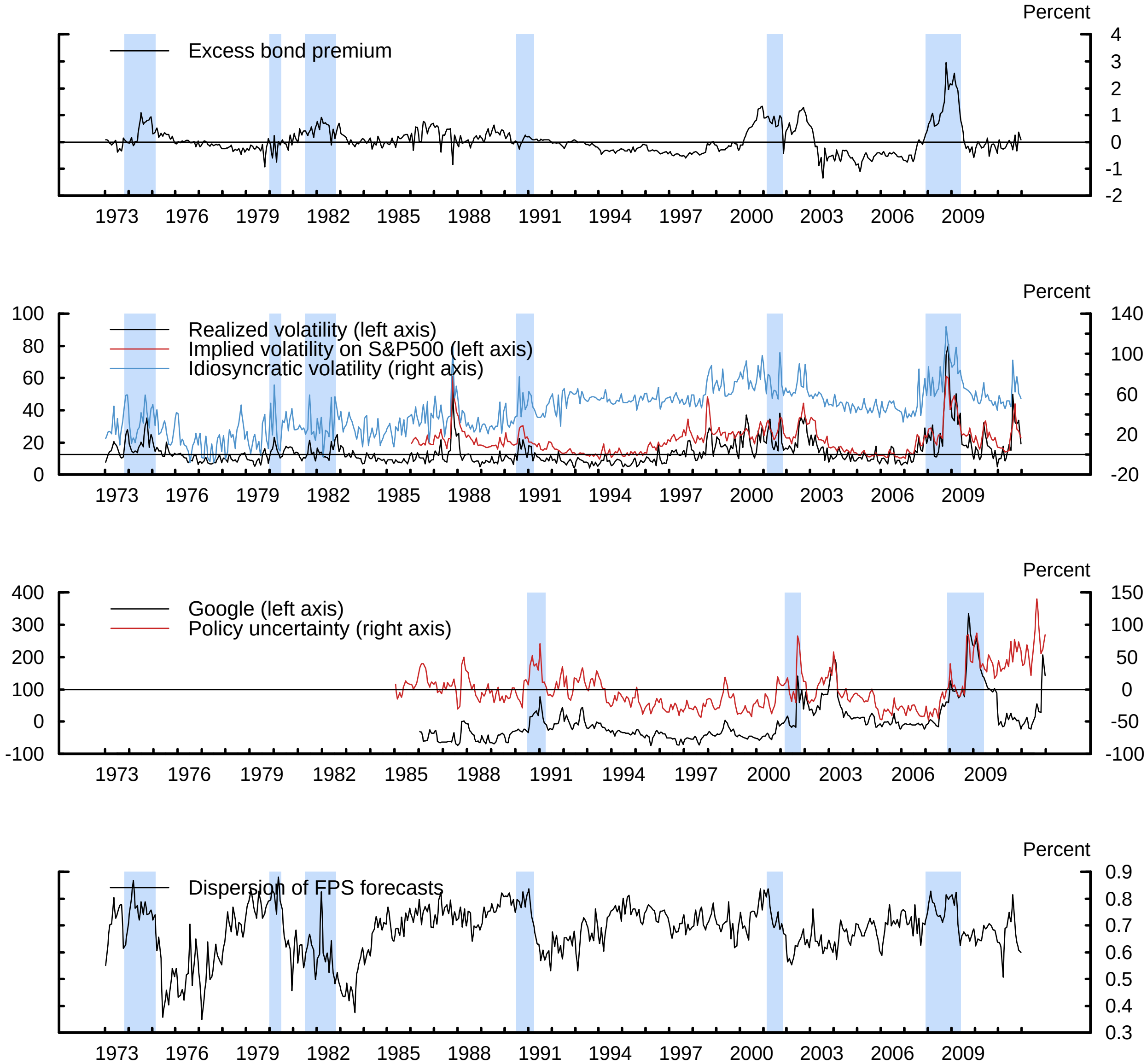
We first analyze the correlation among uncertainty measures and the the proxy for financial distress. Given the correlation structure provided in Table 2, we conclude that all uncertainty proxies present medium to high correlation with the exception of the survey disagreement measure. The correlation between uncertainty proxies and the excess bond premium is 40-60% for all uncertainty measures but the survey disagreement measure. The correlation between the latter and the financial distress proxy is only 26%. The relatively large correlations between uncertainty and the excess bond premium invite to investigate further the link between uncertainty and financial distress by means of Granger (1969) causality tests.

Table 2: Correlation

	EBP	RVOL	IVOL	DISP	Google	BBD	VXO
EBP	1	0.56	0.36	0.26	0.50	0.43	0.58
RVOL		1	0.75	0.11	0.64	0.47	0.84
IVOL			1	0.04	0.47	0.29	0.59
DISP				1	-0.09	-0.01	0.19
Google					1	0.57	0.51
BBD						1	0.49
VXO							1

Notes: The sample ranges from 1985:M1 to 2011:M12 for all variables but VXO for which the sample starts in 1986:M1.

Figure 1: Uncertainty and financial distress measures



Given two time series x_t and y_t, the standard Granger (1969) causality test is based on the following regression

$$y_t = \alpha + \sum_{i=1}^{h} \beta_i y_{t-i} + \sum_{j=1}^{k} \gamma_j x_{t-j} + \epsilon_{y,t}, \ t = 1, \ldots, T \tag{10}$$

A test that x_t does not Granger-causes y_t is an F-test of $H_0 : \gamma_j = 0, \forall j$. As suggested by Rossi (2011), we use HAC-robust variance estimates (Newey and West, 1987) in the F-test. We report the sum of estimated coefficients $\sum_{j=1}^{k} \gamma_j$ and the p-value linked to the Granger-causality tests in Table 3. The upper panel in Table 3 tests whether uncertainty Granger-causes financial distress; the lower panel focuses on the excess bond premium Granger-causing uncertainty. We conclude that the excess bond premium Granger-causes all uncertainty measures but the survey disagreement measure. All uncertainty proxies except for the survey disagreement measure and the economic uncertainty policy index Granger-cause the excess bond premium. These reduced-form results raise questions such as: is uncertainty key in the transmission of financial distress? is the financial channel essential for the transmission of economic uncertainty? To further investigate these issues we propose to consider a structural approach where we identify both uncertainty and financial shocks and proceed to analyze their transmission in the U.S. economy.

Table 3: Granger tests

$EBP_t = \alpha + \sum_{i=1}^{2} \beta_i EBP_{t-i} + \sum_{j=1}^{k} \gamma_j \sigma_{t-j} + \epsilon_t$						
σ	RVOL	IVOL	DISP	Google	BBD	VXO
k	2	1	1	2	2	2
$\sum_{j=1}^{k} \gamma_k$	0.0017	0.0025	0.1294	-0.0003	-0.0004	0.0022
95% CI	[-0.0074, 0.0109]	[0.0004, 0.0046]	[-0.3245, 0.5833]	[-0.0030, 0.0024]	[-0.0066, 0.0057]	[-0.0151, 0.0195]
p-value for F-test	0.0001	0.0202	0.5753	0.0509	0.1753	0.0005
$\sigma_t = \alpha + \sum_{i=1}^{h} \beta_i \sigma_{t-i} + \sum_{j=1}^{k} \gamma_j EBP_{t-j} + \epsilon_t$						
σ	RVOL	IVOL	DISP	Google	BBD	VXO
h	2	2	2	1	1	1
k	1	1	1	1	1	1
$\sum_{j=1}^{k} \gamma_k$	3.8103	3.0496	0.0044	7.6933	4.2704	2.1840
95% CI	[0.5907, 7.0300]	[0.4121, 5.6871]	[-0.0050, 0.0139]	[1.3873, 13.9993]	[1.3174, 7.2238]	[0.7936, 3.5743]
p-value for F-test	0.0205	0.0236	0.3567	0.0170	0.0047	0.0022

Notes: The sample ranges from 1985:M1 to 2011:M12 for all variables but VXO for which the sample starts in 1986:M1. The linear regression models are estimated using HAC-robust variance estimates. A test that σ_t does not Granger-cause EBP_t is an F-test of $H_0 : \gamma_j = 0, \forall j$.

3. Identification

Let us consider a VAR(p) model

$$Y_t = B_0 + B_1 Y_{t-1} + \ldots + B_p Y_{t-p} + u_t \tag{11}$$

where Y_t is an $n \times 1$ vector and u_t is the vector of one-step ahead forecast errors with variance-covariance matrix $\mathbb{E}\left[u_t u_t'\right] = \Sigma$. We estimate the VAR model using Bayesian techniques. In particular, we assume a Minnesota prior à la Doan et al. (1984a) with hyperparameters set as in Fuentes-Albero and Melosi (2012) by optimizing the model fit over a pre-sample of size 24 months. We report the hyperparameters used in Table **??**. We generate 50,000 draws from the posterior[3] and discard the first 10,000 when implementing the identification strategy.

The moving average representation of the finite VAR stated in (11) is given by

$$Y_t = \left[B(L)\right]^{-1} u_t = C(L) u_t \tag{12}$$

Identification schemes decompose the reduced form errors u_t into n mutually orthogonal innovations ε_t with $\mathbb{E}\left[\varepsilon_t \varepsilon_t'\right] = I$. Thus, identification reduces to find a mapping A between the prediction errors and the structural shocks $u_t = A\varepsilon_t$. Let $\widetilde{A}$ be a decomposition of the mapping A. It could be, for example, the Cholesky decomposition or the QR decomposition. Then, there is an orthonormal matrix Q such that $A = \widetilde{A}Q$. Identification is, then, related to specifying such an orthonormal matrix. The penalty function proposed by Faust (1998) and extended by Uhlig (2003) consists of searching for innovations, that is, columns of the orthonormal matrix Q, accounting for the maximal amount of the FEV of a target variable i over a given horizon $[\underline{k}, \overline{k}]$.

Let us define the k-step ahead forecast error for the target variable i as

$$y_{i,t+k} - \mathbb{E}_t\left[y_{i,t+k}\right] = e_i' \left[\sum_{j=0}^{k-1} C_j \widetilde{A} Q \varepsilon_{t+k-j}\right] \tag{13}$$

where $e_i = [0, \ldots, 0, 1, 0, \ldots, 0]'$ where the non-zero element is the $i - th$ element. To search for the largest shock accounting for the maximal amount of the FEV of variable i reduces to find the vector of unit length q_1, that is a column of Q, solving the following optimization

[3] The model is non-stationary for some problems but this is not problematic given that the posterior is well defined. Moreover, as highlighted by Sims and Uhlig (1991), inferences does not depend on stationarity.

program

$$\max_{q_1} e_i' \left[\sum_{k=\underline{k}}^{\overline{k}} \sum_{j=0}^{k-1} C_j \widetilde{A} q_1 q_1' \widetilde{A}' C_j' \right] e_i = q_1' S q_1$$
$$s.t.\ q_1' q_1 = 1$$

where $S = \sum_{k=\underline{k}}^{\overline{k}} \sum_{j=0}^{k-1} \widetilde{A}' C_j' e_i e_i' C_j \widetilde{A}$. The Lagrangian associated with the optimization problem is given by

$$L = q_1' S q_1 - \lambda \left(q_1 q_1' - 1 \right) \tag{14}$$

so that the first order condition is just the definition of an eigenvalue decomposition with q_1 being the eigenvector of S corresponding to the eigenvalue λ. The partition q_1 of the orthonormal matrix Q is the eigenvector linked to the largest eigenvalue λ. This identification strategy is purely statistical. Thus, the researcher must provide an interpretation for the extracted shocks.

One of the appealing features of the statistical approach described above is that we can interpret the standard recursive ordering approach to identification as being the result of using the penalty function. Moreover, recursive orderings also require taking a stand regarding the economic interpretation of the identified shocks. In this case, a shock to the excess bond premium is assumed to be a financial shock and a shock to the uncertainty proxy to be an uncertainty shock. Let us assume that we order the excess bond premium first and the uncertainty proxy second in the VAR model. In this case, a financial shock is the largest shock accounting for 100% of the FEV of the excess bond premium upon impact, that is, $\underline{k} = \overline{k} = 0$. An uncertainty shock is the largest shock accounting for the largest share of the FEV of the uncertainty proxy upon impact and delivering a zero response upon impact for the excess bond premium. In practice, this uncertainty shock accounts for almost 100% of the FEV of the uncertainty proxy. If we revert the ordering, we identify the uncertainty shock without imposing any zero restrictions and we need to impose a zero restriction upon impact for the uncertainty proxy when identifying the financial shock.

The identification approach we propose in this paper is also a two-step procedure that resembles the recursive ordering approach. In fact, our two-step identification scheme can be interpreted as a perturbation of recursive orderings as described above. Let us first identify the largest shock optimizing the criterion function for the excess bond premium for $\underline{k} = 0$ and $\overline{k} = 3$ months. Let us label this shock as the *financial shock*. Note that this shock is an unconditional financial shock. In a second step, we search for the largest shock, orthogonal to the *financial shock*, maximizing the criterion function for the uncertainty proxy for $k \in [0, 3]$. We refer to this shock as a *non-financial related uncertainty shock* so as to make the reader aware of the fact that it captures exogenous variation in uncertainty not encompassed in the shock accounting for the largest share of the FEV of the excess bond premium. That is, the *non-financial related uncertainty shock* is conditional on the *financial shock* extracted in the first step. It is noteworthy that with this identification scheme we are identifying the most powerful financial shock possible within the system. We also proceed to revert the order so we identify the most powerful uncertainty shock within the system. In particular, we first identify the largest shock accounting for the maximal amount of the FEV of the uncertainty proxy over the three-month horizon and label this shock as the *uncertainty shock*. In a second step, we search for the largest shock, orthogonal to the *uncertainty shock*, optimizing the criterion function for the excess bond premium for $k \in [0, 3]$. We refer to this shock as a *non-uncertainty related financial shock* since it is conditional on the *uncertainty shock*. We can also refer to the *financial shock* as an unconditional financial shock and to the *non-uncertainty related financial shock* as a conditional financial shock. Similarly, the *uncertainty shock* is an unconditional uncertainty shock and the *non-financial uncertainty shock* is a conditional uncertainty shock.

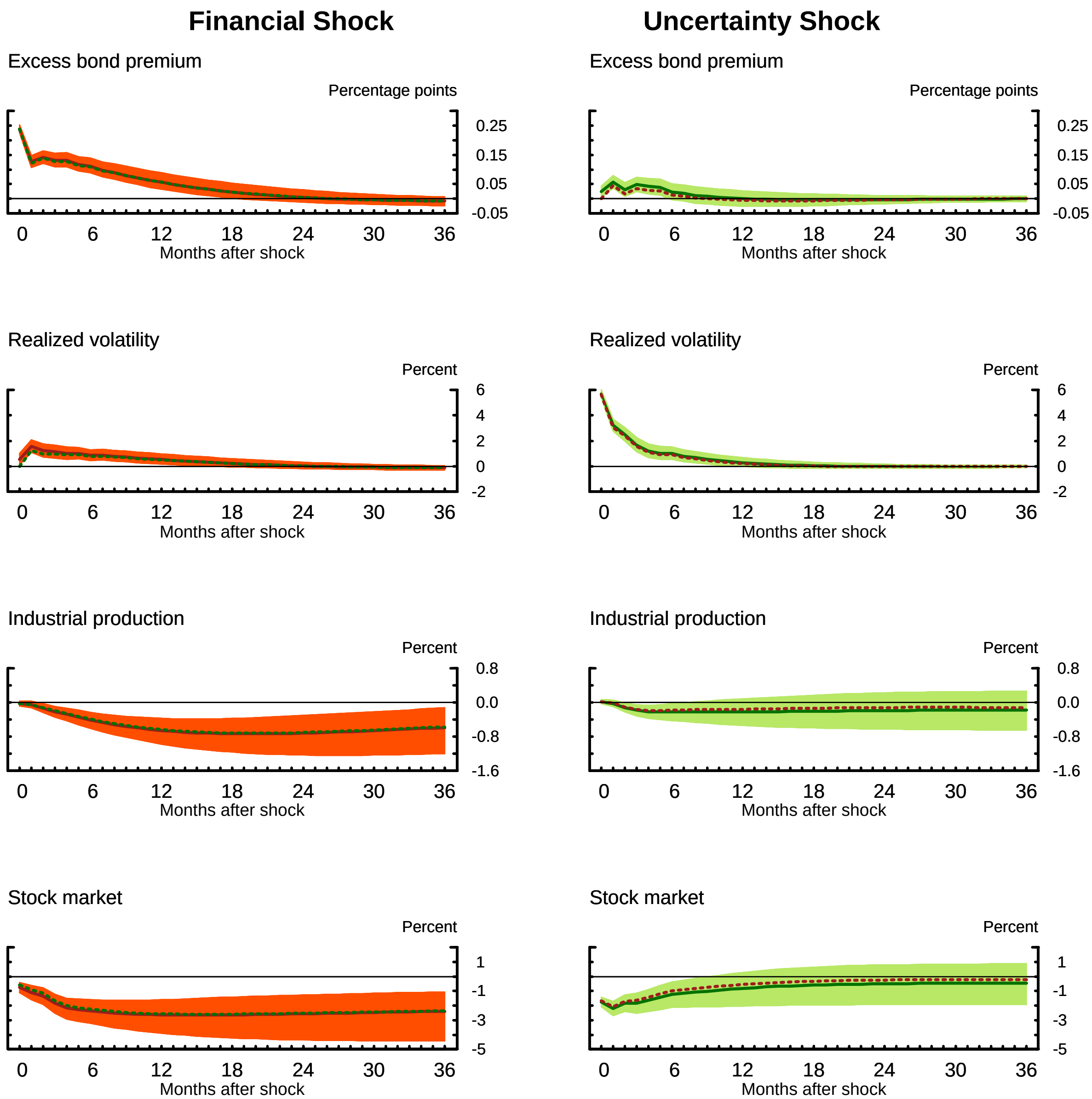
4. Results

4.1. Recursive orderings

Figure 2 reports the impulse response functions to financial and uncertainty shocks identified using recursive orderings. In the left panel, the solid red line and the red band correspond to the median response and its 95% confidence interval when the excess bond premium is ordered first. The dashed green line represents the median response when the excess bond premium is ordered second. In the right panel, the solid green line and the green band correspond to the median response and its 95% confidence interval when realized volatility is ordered first. The dashed red line represents the median response when realized volatility is ordered second. The similarities across orderings in the transmission of both financial and uncertainty shocks are remarkable, pointing toward an irrelevance of the ordering chosen for these two variables.

An unanticipated increase of one standard deviation in the excess bond premium generates sizable adverse macroeconomic effects. The responses for real variables are lagged, slowly-building, and very persistent. In particular, while the response upon impact for the industrial production index is not significantly different from zero; it bottoms out about 0.75 percentage points below trend 20 months after the shock and it is 0.60 percentage points below trend even 36 months after the shock. The recessionary effects of uncertainty shocks are also long-lasting but significantly milder. Output response bottoms out about 0.30 percentage points below trend 4 months after the shock and it stabilizes around 0.20 percentage points below trend. It is noteworthy that the response to uncertainty shocks is not significantly different from zero starting 6 months after the shock.

Figure 2: Impulse Response Functions: Recursive orderings

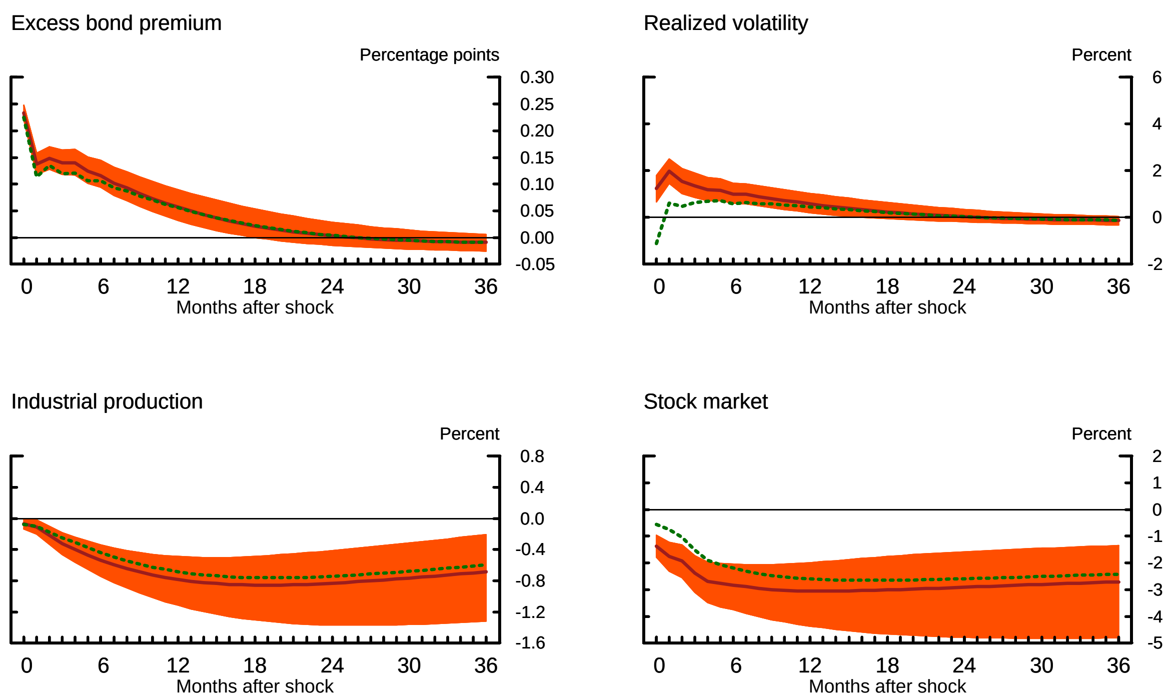


An uncertainty shock generates a collapse in the stock market of 1.5 percentage points below trend upon impact, while the initial response of stock market returns to a financial shock is less than 1 percentage points below trend. However, while the stock market starts recovering from uncertainty shocks after one month, the disruption linked to financial shocks is slowly building and bottoms out at around 3 percentage points below trend 18 months after the shock. More importantly, the adverse effects of financial shocks are very persistent. Conversely, the stock market recovers from uncertainty shocks in about 10-12 months after the shock given that the responses are no longer significantly different from zero.

4.2. Two-step Penalty Function

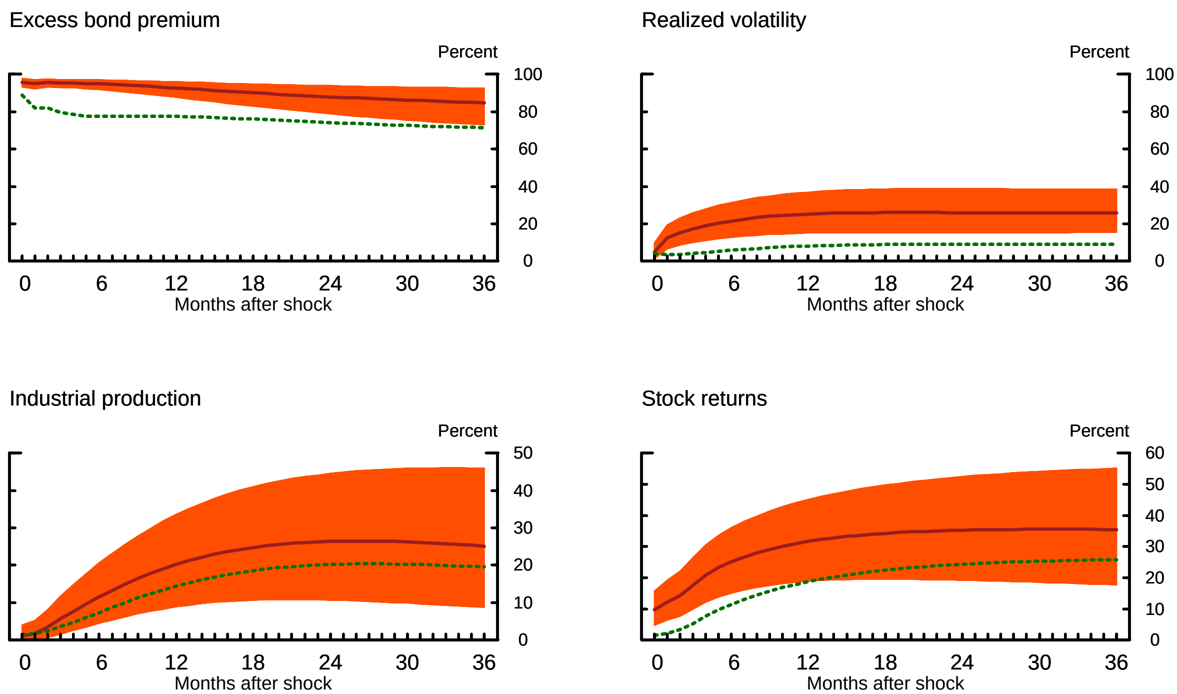
We report the responses to financial shocks in Figures 3 and 8. The red solid line represents the response to a *financial shock* and the green dashed line is the response to a *non-uncertainty related financial shock*. That is, the responses to an unconditional financial shock are in red and to a conditional financial shock are in green. The red bands represent the 95% confidence bands for the response to an unconditional financial shock.

Figure 3: Impulse Response Functions: Penalty function. Financial shock



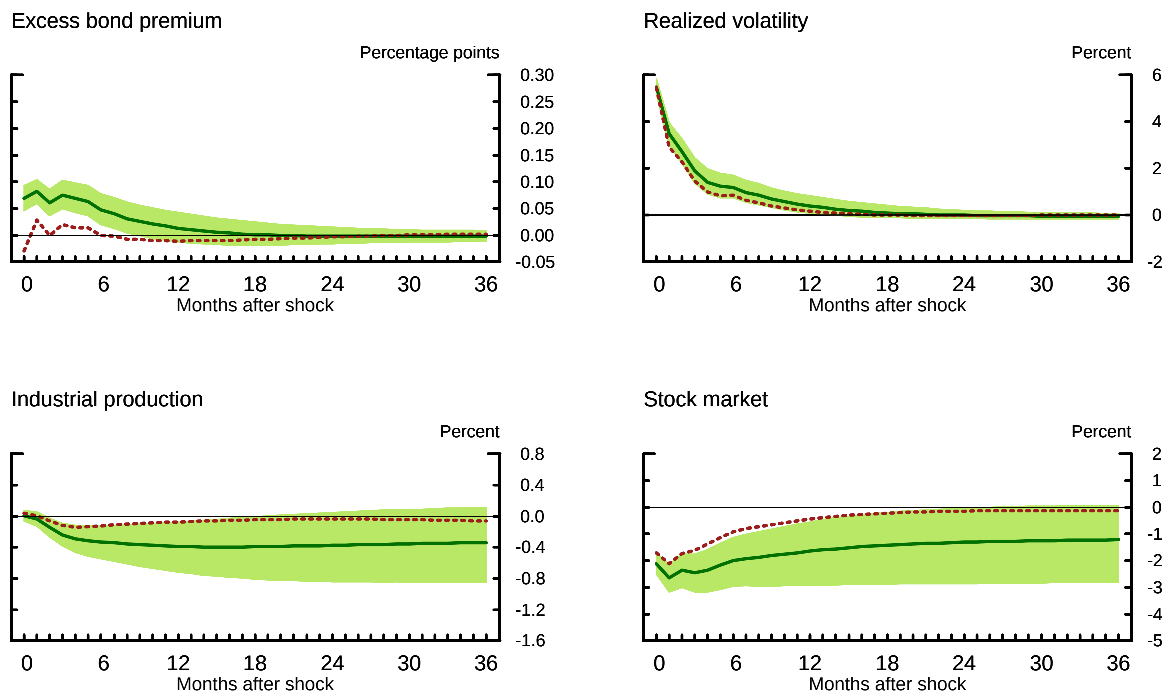
The responses to both types of financial shocks are qualitatively and quantitatively similar. The only variable with significantly different responses to the two types of financial shocks is stock market returns during the first 4 months after the shock. Our results point toward a lagged effect of financial shocks since the responses upon impact for all variables but RVOL and stock returns are not significantly different from zero. Thus, we get zero responses upon impact as a result of our identification scheme and not as an assumption of the identification strategy. An adverse financial shock generates a large and long-lasting recession. In particular, an increase of one standard deviation in the excess bond premium translates into a collapse of the level of industrial production that bottoms out about 0.8 percentage points below trend 18 months after the shock when considering *financial shocks* and about 0.75 percentage points after a *non-uncertainty related financial shock*. Employment bottoms out about 0.35 percentage points below trend 24 months after a *financial shock* and almost 0.3 percentage points after a *non-uncertainty related financial shock*. It is noteworthy that the recovery after both types of financial shocks is very slow since it is far from being over even 36 months after the shock. Both types of financial shocks generate a continuous disinflation and a collapse of short-term rates that bottoms out about 0.2 percentage points 18 months after the shock. Financial shocks generate a collapse in the stock market of about 0.5-1.5%, which slowly worsens over time so that stock market returns are 3% below trend 36 months after the shock.

Figure 4: Forecast Error Variance: Penalty function. Financial shock



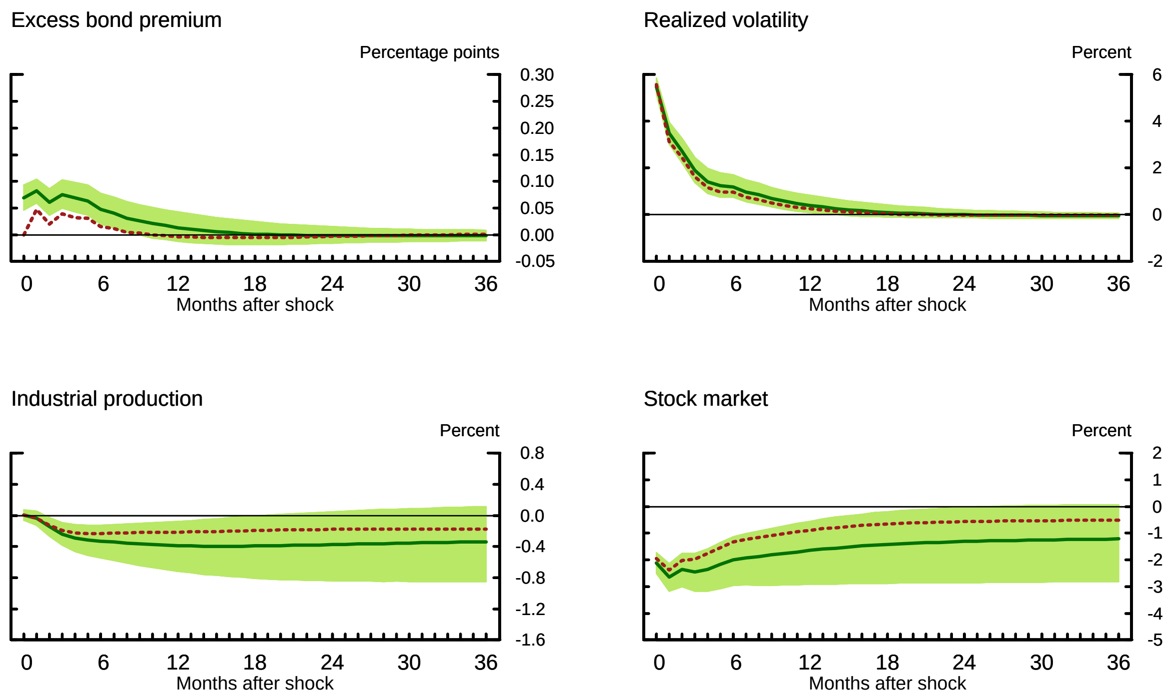
We explore the relative importance of financial shocks in driving economic activity in Figures 4 and 11. We should highlight that while the unconditional financial shock explains 95% of the FEV of the excess bond premium upon impact, the conditional financial shock does account for 85% of it. At the 36-month horizon, the conditional financial shocks explains 75% of the forecast error variance in the excess bond premium. This relatively large role played by conditional financial shocks in accounting for the variability of the excess bond premium explains the similarities in the transmission of financial shocks across identification schemes. At the 36-month horizon, financial shocks account for 20-25% of the forecast error variance in the industrial production index and 20-30% of the variability in employment. The role in driving nominal variables reduces to in between 5% and 10%. While *non-uncertainty related financial shocks* explain 25% of the FEV of stock market returns, *unconditional financial shocks* account for 35% of its variability at the 36-month horizon. Financial shocks play a non-negligible role in driving realized volatility since they explain 30% of that when identified first and 10% of the FEV of the uncertainty measure if the financial shock is conditional on the uncertainty shock. Given that the relative role played by financial shocks in driving economic activity does not dramatically decrease when considering *non-uncertainty related financial shocks*, we conclude that the uncertainty channel is not too relevant in the transmission of financial shocks in the U.S. economy.

Figure 5: Impulse Response Functions: Penalty function. Uncertainty shock



Figures 5 and 9 report the impulse response functions to an unconditional *uncertainty shock* in solid green and to a *non-financial uncertainty shock* in dashed red. If the uncertainty shock is identified first, that is, the financial channel is fully operating, an adverse shock translates into a long-lasting collapse of 0.4 percentage points below trend. It is noteworthy that the adverse economic effects of unconditional *uncertainty shocks*, which are the most powerful uncertainty shocks affecting the system under analysis, are half of those due to financial shocks. When the uncertainty shock is identified second, the response of production bottoms out about 0.2 percentage points below trend 6 months after shock after which, the economy recovers in about 10 months. Both uncertainty shocks translate into a reduction in stock market returns of about 2%. If uncertainty shocks are transmitted through the financial channel, then the recovery from the collapse in the stock market is very slow. In particular, 36 months after the shock, the stock market is still 1% below trend. However, the recovery after a conditional uncertainty shock is complete 18 months after the shock. We conclude that the financial channel seems to be key in the transmission mechanism of uncertainty shocks.

Figure 6: Impulse response function: Restricted Penalty function. Uncertainty shock

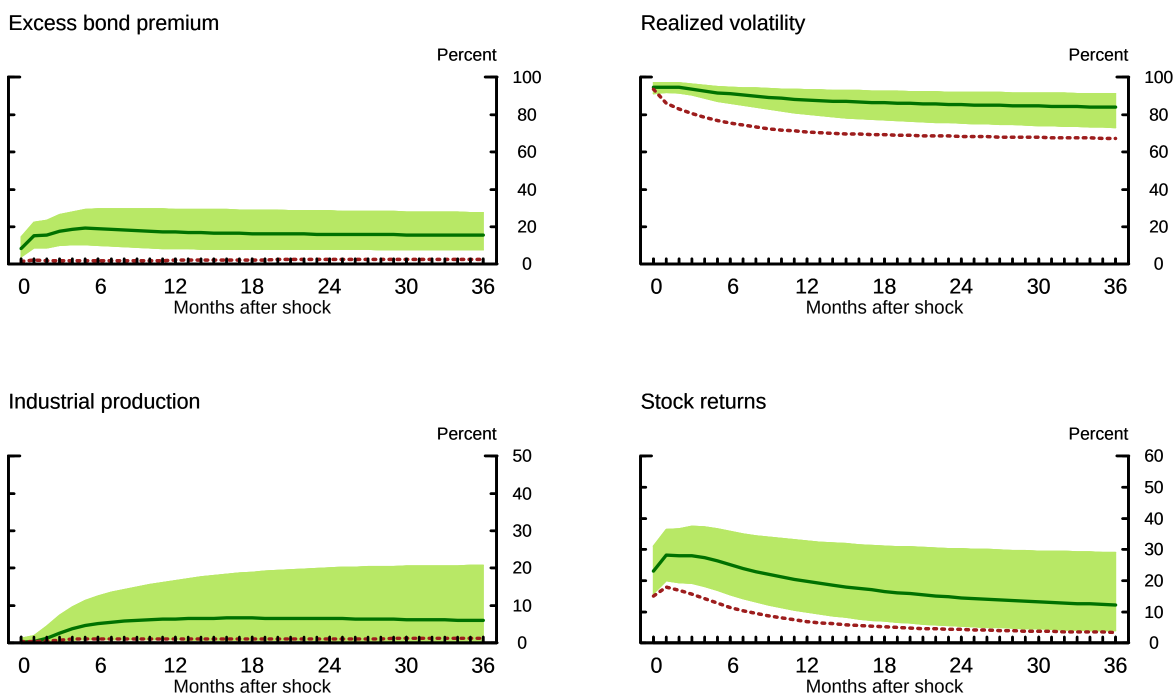


In order to investigate further the relative role played by the financial channel in the propagation of uncertainty shocks, we proceed to close the financial channel. In particular, we use the penalty function approach to identify uncertainty shocks but imposing a zero response upon impact for the excess bond premium. We report in Figures RVOL-restricted and 10 the impulse responses to an uncertainty shock identified as the largest shock accounting for the maximal amount of the forecast error variance of RVOL over a three-month horizon and generating a zero response upon impact for EBP using red dashed lines. We also report the responses to an unconditional uncertainty shock in solid green. Thus, we are comparing the most important driver of uncertainty over the first quarter after the shock when freely transmitted through the financial channel and when the financial channel is not operational upon impact. The restriction imposed in enough to reduce the size of the adverse persistent economic effects to a half, which highlights the key role played by the financial channel in the transmission mechanism of uncertainty shocks.

To test the validity of the exercise on identifying uncertainty shocks using a restricted penalty function approach, we implement the same approach to identify financial shocks. That is, we search for the largest shock accounting for the maximal amount of variation in EBP over the first quarter subject to generating a zero response in uncertainty upon impact. The responses are quite similar to the ones obtained when financial shocks are identified first with the unrestricted penalty approach. These results confirm two of our previous statements: *(i)* the uncertainty channel plays an almost negligible role in the transmission of financial shocks and *(ii)* the relevance of the financial channel for the transmission of uncertainty shocks confirmed by the restricted penalty approach is not an artifact of imposing a zero restriction but inherent to the data.

The relative role by uncertainty shocks as drivers of realized volatility are very similar across identification schemes. In particular, both uncertainty shocks account for 95% of the FEV of realized volatility and in between 65% and 85% at the 36-month horizon. The role played in driving economic fluctuations, however, is quite sensitive to whether uncertainty shocks are unconditional or conditional on financial shocks. While unconditional uncertainty shocks play a non-negligible role driving real economic aggregates, the financial distress proxy, and stock market returns; the relative importance of uncertainty shocks is reduced to a minimum if they are identified second. Regardless of the identification scheme, uncertainty shocks play a negligible role in driving nominal variables.

Figure 7: Forecast Error Variance: Penalty function. Uncertainty shock



5. Robustness

In this section, we perform several robustness exercises. We focus our discussion on the responses of the industrial production index but the results carry over the other variables under analysis. First, we study the sensitivity of our results to the sample under analysis. In Figure 14, we report the impulse response functions for both identification schemes for the entire sample (1973-2012), the most recent sub-sample (1985-2012), and the most recent sub-sample excluding the last recession (1985-2012). The responses to financial shocks qualitatively similar. It is remarkable that excluding the 1970s translates into a relatively stronger effect of financial shocks in real economic activity. The response of the industrial production index to both types of financial shocks bottoms out at about 1.2 percentage points below trend. Thus, the size of the recession is 50% larger than when the VAR model is estimated using the entire data set.

The responses to uncertainty shocks are more sensitive to the sample under analysis. While unconditional uncertainty shocks have persistent effects in real economic activity if the 1970s are included in the sample, the recovery starts 6 months after the shock when only post-1985 data is considered. The sensitivity to the sample is even more dramatic for uncertainty shocks conditional on financial shocks. *Non-financial uncertainty shocks* generate economically significant adverse effects for, at least 6 months, when the 1970s are included in the data sample. If we only consider post-1985 data, the response of the industrial production index is not significantly different from zero for several months until expansionary effects are put in place. At the 36-month horizon, the industrial production index is almost 0.4 percentage points above trend. These results highlight that the relative importance of the financial channel in the transmission of uncertainty shocks has increased over time.

We also revisit the transmission of financial and uncertainty shocks when alternative proxies for uncertainty are included in the VAR. In particular, we re-estimate the VAR models for each of the uncertainty proxies discussed in Section 2 and identify uncertainty and financial shocks by means of the two-step penalty approach discussed in Section 3. To economize in figures, we report, in figure 15, a comparison across models of the responses of the industrial production index for the sample 1985-2012, with the exception of the baseline that refers to the sample 1973-2012. There is more quantitative and qualitative diversity in the response to uncertainty shocks than to financial shocks. The responses to a conditional uncertainty shock range from those implying a long-lasting recession to those delivering a sizable and persistent expansion.

6. Conclusions

This paper explores the transmission mechanism of financial and uncertainty shocks. To do so, we propose a statistical approach to identification based on the penalty function in an attempt to discriminate empirically between these two sources of economic fluctuations. We show that while recursive orderings deliver similar responses to both shocks, a small perturbation of recursive orderings is enough to deliver distinct responses. In particular, adverse financial shocks are followed by slowly-building recessions and slow recoveries. The transmission mechanism of uncertainty shocks is very sensitive to the identification scheme, the sample, and the uncertainty proxy. We conclude that uncertainty shocks can deliver a long-lasting sizable recession as long as they are transmitted through a financial channel. Once we close the financial channel, the adverse effects of uncertainty shocks are significantly milder. Regardless of the interpretation given to the statistically extracted shocks, we can argue that there is more informational content regarding the sources of aggregate fluctuations in the excess bond premium than in the uncertainty proxy under consideration. We can take these results a step further to raise awareness among modelers on the importance of including a financial channel when incorporating uncertainty shocks to macro models.

References

Bachmann, R., Elstner, S., Sims, E., 2012. Uncertainty and economic activity: Evidence from business survey data. American Economic Journal: MacroeconomicsForthcoming.

Baker, S. R., Bloom, N., Davis, S. J., 2012. Measuring economic policy uncertainty, manuscript, Stanford University.

Bloom, N., 2009. Inside the black box: the credit channel of monetary policy transmission. Econometrica 77 (3), 623–685.

Canova, F., 1994. Were financial crisis predictable? Journal of Money, Credit, and Banking 26, 102–124.

Carhart, M. M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57–82.

Carriero, A., Kapetanios, G., Marcellino, M., 2010. Forecasting government bond yields with large bayesian vars, cEPR Discussion Paper No. 7796.

Doan, T., Litterman, R., Sims, C., 1984a. Forecasting and conditional projection using realistic prior distributions. Econometric Reviews 4 (1), 1–100.

Doan, T., Litterman, R., Sims, C. A., 1984b. Forecasting and conditional projection using realistic prior distributions. Econometric Reviews 3 (1), 1–100.

Donaldson, R. G., 1992. Sources of panics: Evidence from the weekly data. Journal of Monetary Economics 30, 277–305.

Fama, E. F., French, K. R., 1992. The cross-section of expected stock returns. Journal of Finance 47, 427–465.

Faust, J., 1998. The robustness of identified var conclusions about money. Carnegie-Rochester Conference Series on Public Policy 49 (Dec), 207–44.

Fuentes-Albero, C., Melosi, L., 2012. Methods for computing marginal data densities from the gibbs output, mimeo.

Gambetti, L., Musso, A., 2012. Loan supply shocks and the business cycle, eCB Working Paper No 1469.

Giannone, D., Lenza, M., Primiceri, G., 2012. Prior selection for vector autoregressions, nBER Working Paper.

Gilchrist, S., Sim, J. W., Zakrajšek, E., 2012. Uncertainty, financial frictions, and irreversible investment, manuscript.

Gilchrist, S., Zakrajšek, E., 2012. Credit spreads and business cycle fluctuations. American Economic ReviewForthcoming.

Granger, C., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica 37, 424–438.

Meeks, R., 2012. Do credit market shocks drive output fluctuations? evidence from corporate spreads and defaults. Journal of Economic Dynamics & Control 36, 568–584.

Merton, R., 1974. On the pricing of corporate debt: The risk structure of interest rates. Journal of Finance 29, 449–470.

Nason, J. M., Tallman, E. W., 2012. Business cycles and financial crisis: The roles of credit supply and demand shocks, federal Reserve Bank of Cleveland Working Paper 12-21.

Newey, W. K., West, K. D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 817–858.

Popescu, A., Smets, F. R., 2010. Uncertainty, risk-raking, and the business cycle in germany. CESifo Economic Studies 56 (4/2010), 596–626.

Rossi, B., 2011. Advances in forecasting under instabilities. In: Elliott, G., Timmermann, A. (Eds.), The Handbook of Economic Forecasting. Vol. 2. Elsevier-North Holland Publications, Amsterdam, The Netherlands.

Sims, C. A., Uhlig, H., 1991. Understanding unit rooters: A helicopter tour. Econometrica 59, 1591–1599.

Sims, C. A., Zha, T., 1998. Bayesian methods for dynamic multivariate models. International Economic Review 39 (4), 949–968.

Stock, J. H., Watson, M. W., 2012. Disentangling the channels of the 2007-2009 recession, brookings Papers on Economic Activity,.

Uhlig, H., 2003. What moves real gnp?, manuscript. Humbolt University, Berlin.

appendix

Minnesota prior

Let us rewrite the VAR model in equation (11) as

$$Y = X\Phi + U,\ U \sim \mathcal{N}(\mathbf{0}, \Sigma) \tag{15}$$

The Minnesota prior put forward by Doan et al. (1984b) is based on centering the prior distribution of Φ at a value that implies a random-walk behavior for each of the series in the observable set. In particular, we implement the single-unit-prior suggested by Sims and Zha (1998) through dummy observations. The use of dummy observations allows us to specify plausible correlations between parameters in our prior. The Minnesota prior is conditional on means and standard deviations of a pre-sample and a vector θ of hyperparameters:

1. τ controls the overall tightness of the prior
2. d is used to scale the prior standard deviations for coefficient associated with lagged variables, y_{t-l}, according to l^{-d}
3. w states the number of observations used to obtain the prior for the covariance matrix of error terms.
4. λ is a tuning parameter for coefficients associated with the intercept
5. μ controls the correlation between coefficients

Given that VAR inference is sensitive to the choice of hyperparameters, we set the hyperparameters of the prior so as to maximize the marginal data density as in Giannone et al. (2012) and Carriero et al. (2010).

$$\theta^{\star} = arg\max \int p(Y|\theta, \Sigma)\, p(\Phi, \Sigma|\theta)\, d(\Phi, \Sigma)$$

Given that the use of dummy observations leads to a conjugate prior, we have that the above marginal likelihood of the data has an analytical expression, which reduces the computational burden of the optimization program. Following Fuentes-Albero and Melosi (2012), we perform a stochastic search based on simulated annealing (Judd, 1998) with one million stochastic draws. We perform this procedure on a sample of size 24 months.

Figures

Figure 8: Impulse Response Functions: Penalty function. Financial shock

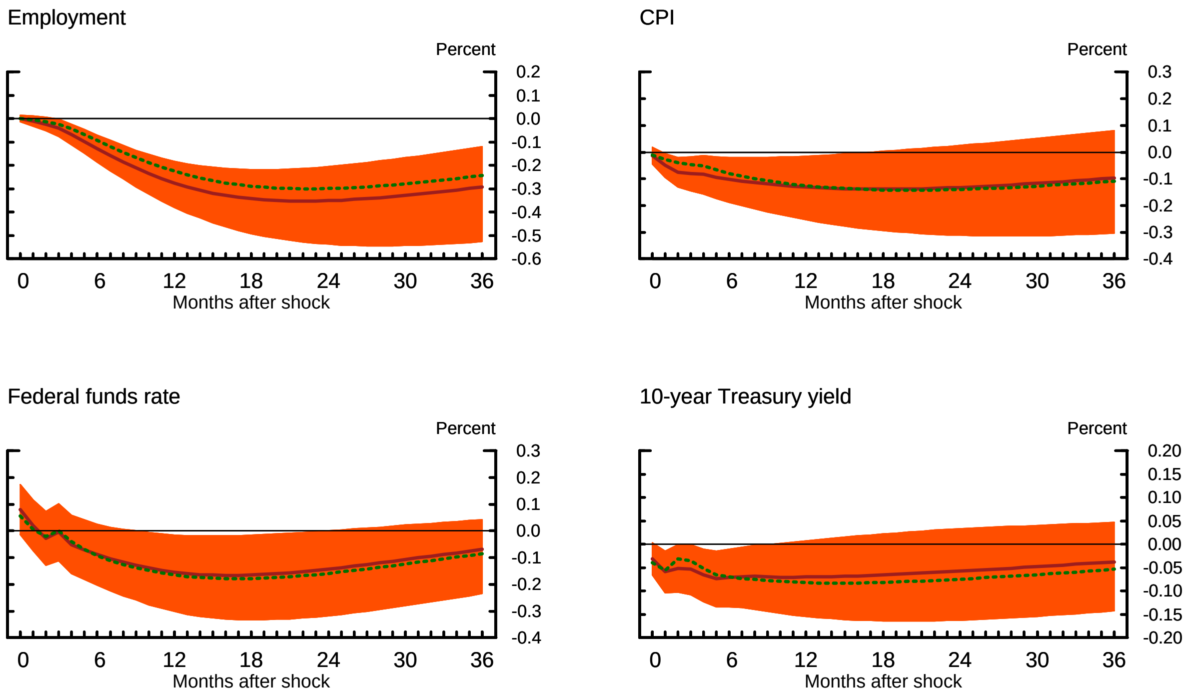


Figure 9: Impulse Response Functions: Penalty function. Uncertainty shock

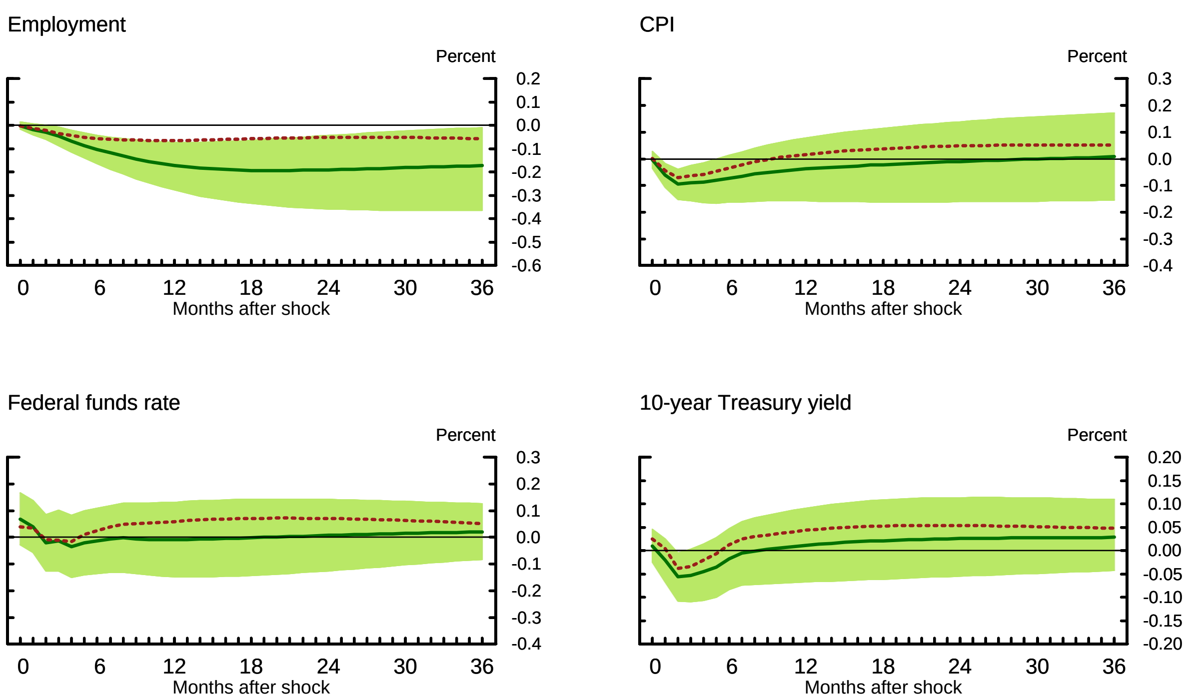


Figure 10: Impulse response function: Restricted Penalty function. Uncertainty shock

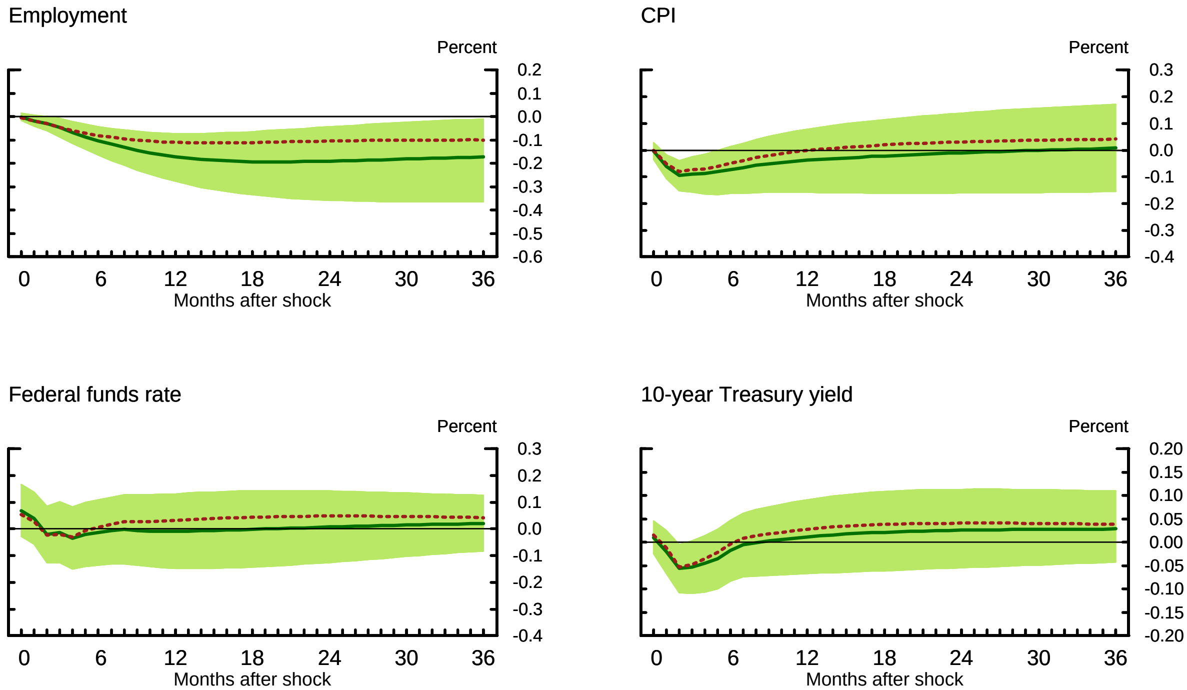


Figure 11: Forecast Error Variance: Penalty function. Financial shock

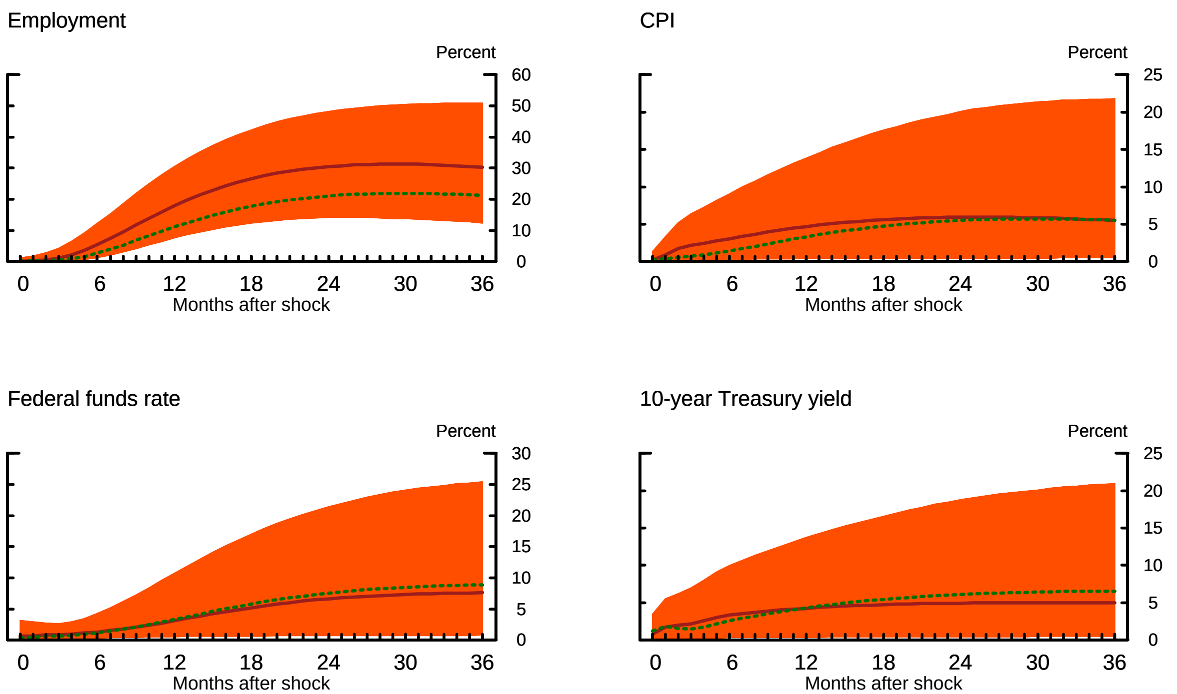


Figure 12: Forecast Error Variance: Penalty function. Uncertainty shock

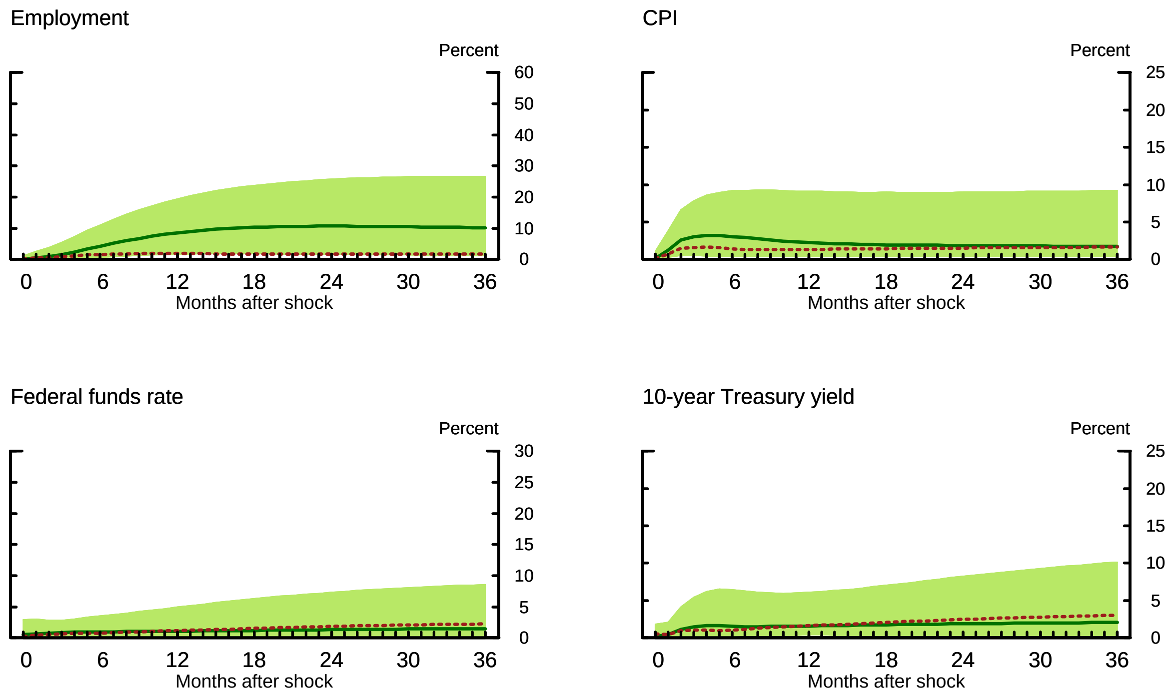


Figure 13: Historical variance decomposition

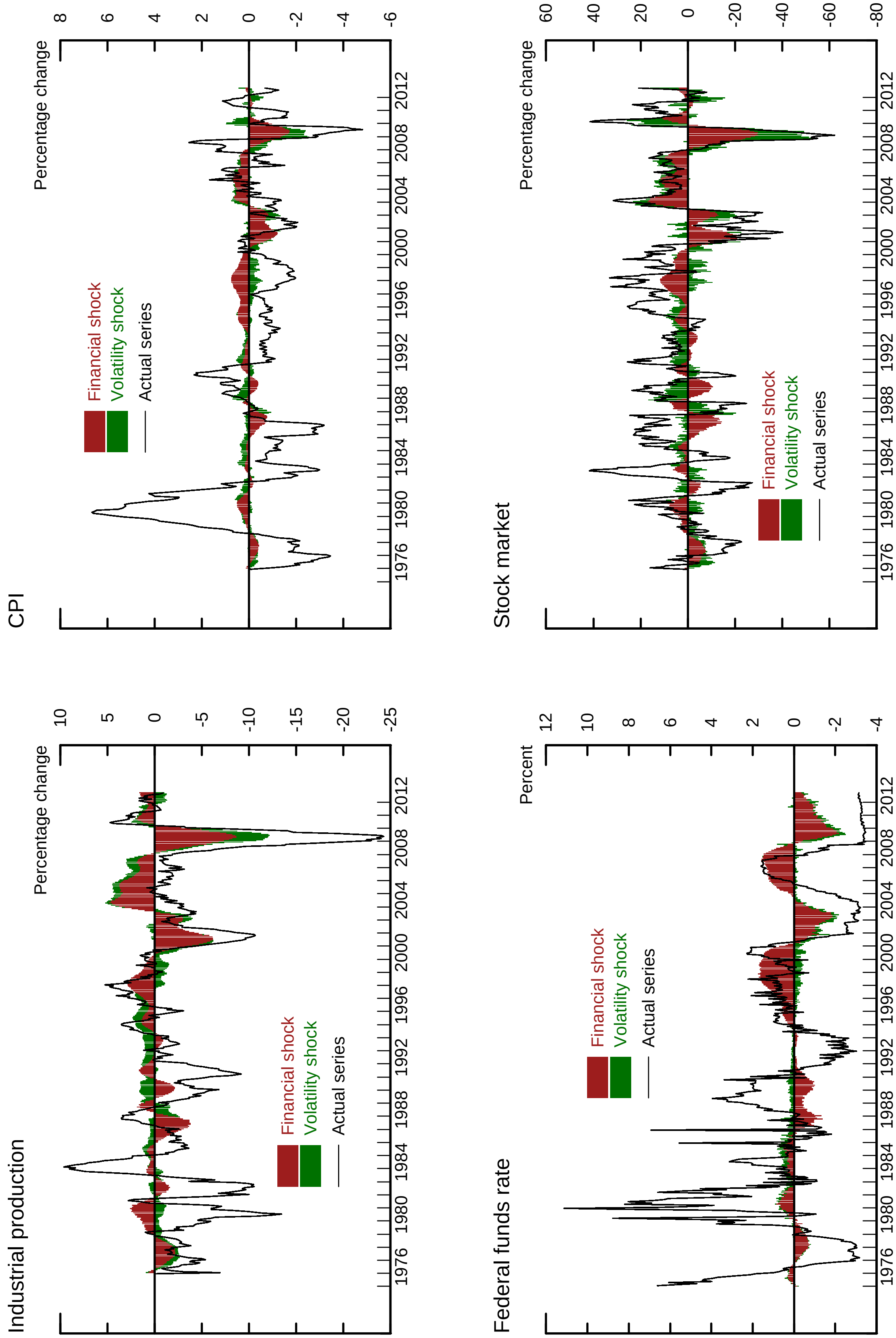


Figure 14: Robustness: IRF for Industrial production index

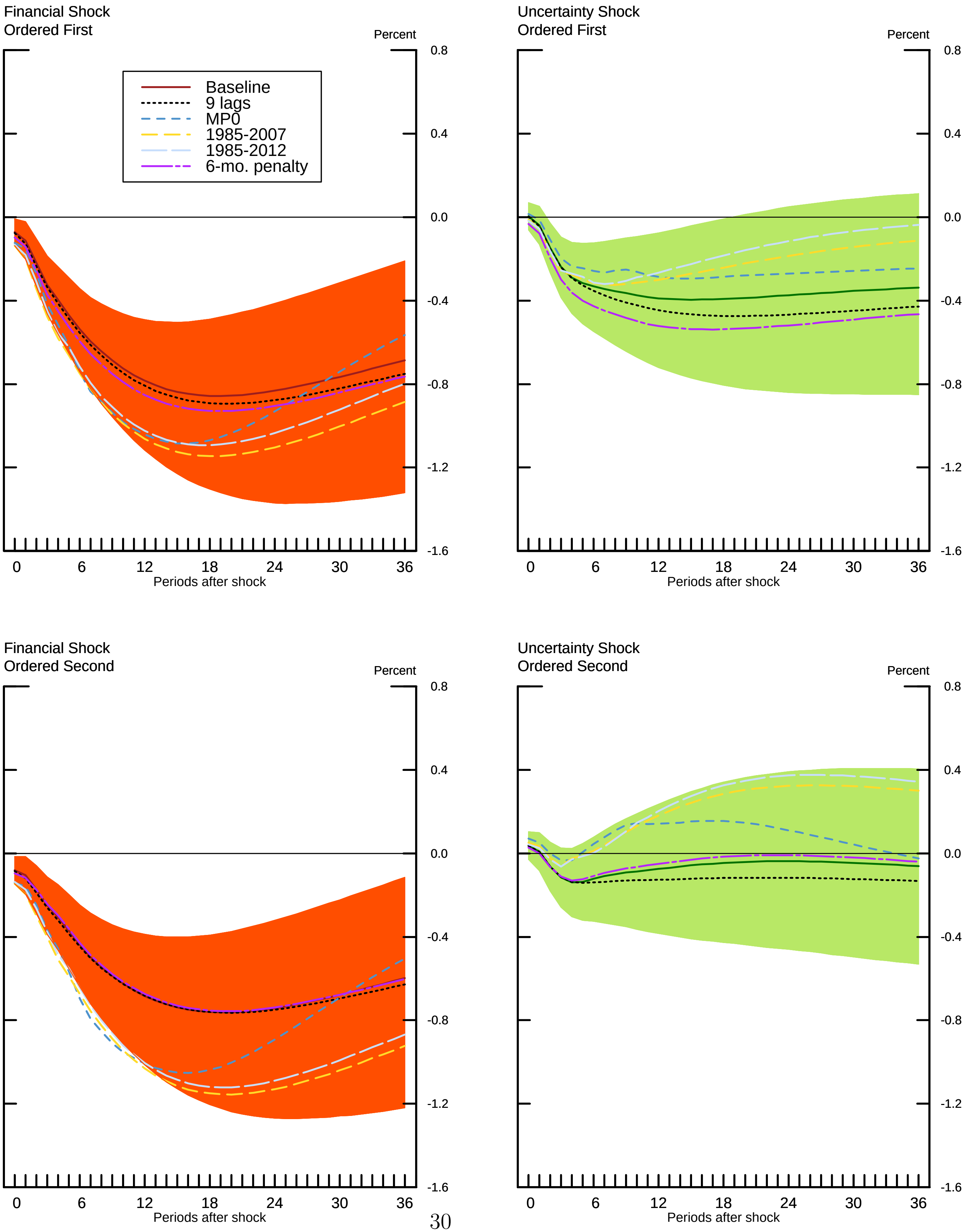


Figure 15: Robustness: IRF for Industrial production index