The Macroeconomic Impact of Financial and Uncertainty Shocks[☆]

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Abstract

There is a consensus about the increasing exposure to disruptions in the financial system and economic uncertainty over the 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 this respect by using a penalty function approach to identification. Our criterion function is such that the structural shock maximizes the response of a target variable over a given horizon. 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, their economic impact is significantly attenuated so that their relative role in driving business cycle fluctuations is not significantly different from zero.

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1. Introduction

The depth and duration of the 2007-2009 recession and the associated turmoil in financial markets has cast doubt on the traditional sources of business cycle shocks. To better understand the extraordinary events of the past several years, researchers have singled out two alternative drivers of economic downturns: financial market disruptions and spikes in economic uncertainty. In practice, however, distinguishing between these two types of economic shocks is difficult because periods of financial market turmoil are generally accompanied by a significant increase in economic uncertainty; at the same time, sudden sharp increases in conventional volatility and risk indicators – widely used proxies for economic uncertainty – are frequently associated with financial market strains. Indeed, in their anatomy of the "Great Recession", Stock and Watson (2012) explicitly poin out the high correlation between indicators of financial distress and economic uncertainty and conclude that "these two sets of instruments do not seem to be identifying distinct shocks".

The identification of financial and uncertainty shocks within a standard vector autoregressive (VAR) framework – the workhorse of empirical macroeconomics – is complicated by the fact that indicators of financial distress and uncertainty are "fast-moving" variables. As a result, it is difficult to impose plausible zero contemporaneous restrictions to identify these two types of shocks. It it also difficult to impose sign restrictions on the impulse response functions in order to achieve an economically plausible identification because financial and uncertainty shocks have the same qualitative effects on prices and quantities.

To identify shocks behind changes in financial conditions and economic uncertainty within a VAR framework, we use the penalty function approach developed by Faust (1998) and extended by Uhlig (2005). Under this approach, a structural disturbance is identified using a criterion that such a shock should maximize the response of a target variable over a given horizon. Given our focus on the role of financial and uncertainty shocks in business cycle fluctuations, we implement the penalty function criterion in two steps. In the baseline identification, we first search for a shock that maximizes the response of the financial target variable over a given horizon – we called this a financial shock. In the second step, we search for an orthogonal shock that maximizes the response of the uncertainty proxy over the same horizon – we called that an uncertainty shock. We also consider an alternative identification scheme that reverts the ordering of the penalty function steps.

In essence, both of our identification schemes assume that the primary cause of changes in financial conditions is a financial shock, while swings in economic uncertainty are primarily due to uncertainty shocks. Compared with the identification schemes that rely on either zero

or sign restrictions, our approach does not impose any restrictions on the response of other endogenous variables in the VAR system, nor does it rule out contemporaneous responses of financial conditions to uncertainty shocks or vice versa[1].

To implement this approach, we consider a standard monthly VAR, augmented with an indicator of financial conditions and a proxy for macroeconomic uncertainty. To measures financial conditions, we use the excess bond premium (EBP), an indicator of the effective risk-bearing capacity of the financial intermediary sector (, Gilchrist and Zakrajšek, 2012). In our baseline identification, we use the realized stock market volatility as a proxy for economic uncertainty because this measure is available over the longest time period. In the robustness analysis, we also examine other indicators of macroeconomic uncertainty, including option-implied volatility of equity returns (Bloom, 2009), the cross-sectional dispersion of survey-based forecasts of macroeconomic indicators (Bachmann, Elstner, and Sims, 2013) and indexes based on the frequency of "uncertainty-related" words or phrases that occur across a large number of news sources (Baker, Bloom, and Davis, 2013).

Our results indicate that financial shocks have a significant effect on the economy: A one standard deviation shock to the EBP leads to a modest but persistent increase in uncertainty and an economically and statistically significant decline in economic activity and bank lending. In addition, the stock market falls substantially, and share prices remain depressed for a considerable period of time. These results are consistent with our maintained assumption that shocks to the EBP are capturing disruptions in the credit-intermediation process. Macroeconomic implications of such financial shocks based on the alternative identification scheme are very similar. This robust feature of financial shocks does not extend to uncertainty shocks, however. We find that uncertainty shocks have a significant macroeconomic impact only under the alternative identification, where they elicit a significant and persistent response of the EBP. In the baseline identification scheme, by contrast, the impact of uncertainty shocks is significantly attenuated and has no effect on financial conditions.

Through the lenses of our baseline identification scheme, these results indicate that failing to control for financial shocks may overstate the macroeconomic effects of uncertainty shocks. The fact that uncertainty increases upon impact in response to a financial shock suggests that swings in uncertainty are influenced importantly by changes in financial conditions. Through the lenses of the alternative identification scheme, our findings indicate that uncertainty

[1]It is worth emphasizing that our approach differs from the standard sign restriction identification schemes in that we identify a single structural model rather than a set of models; see Arias et al. (2013) for a detailed discussion

shocks have sizable effects on the real economy, especially in circumstances when they induce a concomitant deterioration in financial conditions.

Related literature: In the VAR literature, financial shocks have been identified using sign or zero restrictions. Gilchrist and Zakrajšek (2012) assume that shocks to the EBP affect real variables and inflation with a lag but they have contemporaneous effects on risk-free rates and stock prices. Using a time-varying parameter VAR model, Prieto et al. (2013) identify financial shocks assuming that shocks to credit spreads affect economic activity and inflation in the real and housing sector with a lag, while stock prices and risk-free rates can react contemporaneously to such shocks. Boivin et al. (2013) explore identification of credit shocks in data-rich environments. They first estimate a factor augmented vector autoregressive (FAVAR) model on a monthly balanced panel and assume that CPI inflation, the unemployment rate, and the federal funds rate are the only indicators that do not respond upon impact to a surprise in the B-spread. Second, they estimate a FAVAR on an unbalanced (mixed frequency) panel and assume that inflation, the unemployment rate, and consumption growth do not respond upon impact but investment and the federal funds rate are allowed to respond. Finally, they estimate a FAVAR on a balanced quarterly panel and identify credit shocks using sign restrictions. They impose that after an adverse credit shock, the responses of PCE inflation, GDP growth, consumption growth, and investment growth must be non-positive. Moreover, the response of nonresidential investment growth must be larger than the response of consumption growth. Meeks (2012) estimates a VAR model on monthly data including expected default rates and a high yield bond spread. 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. Gambetti and Musso (2012) use sign restrictions to identify credit supply shocks in a time-varying parameters VAR model with stochastic volatility. In particular, they assume that an expansionary loan supply shock leads to an increase in GDP, an increase in loans, and a fall in lending rates. Given our results, we can argue that these sign restrictions could also characterize the responses to an uncertainty shock.

The empirical literature on uncertainty relies mostly on zero restrictions to identify uncertainty shocks. In his seminal paper, Bloom (2009) identifies uncertainty shocks by placing the uncertainty proxy – a stock market volatility index – after stock market returns but before the real and nominal block. Thus, the transmission of uncertainty shocks through equity markets is assumed to be impaired upon impact. Consequently, uncertainty shocks in Bloom (2009) have a negligible effect on economic activity upon impact. Once the financial channel is open – one period after the shock –, uncertainty shocks have an economically significant

effect on real variables. Baker et al. (2013) proceed by placing a policy uncertainty index before stock market returns, the federal funds rate, employment, and industrial production. Therefore, uncertainty shocks affect contemporaneously financial markets. They conclude that uncertainty shocks have persistent and significantly recessionary effects in real variables. Bachmann et al. (2013) use a survey-based dispersion measure to proxy for uncertainty and order it first in the VAR. They also conclude that uncertainty shocks generates initially small effects but the recessionary effects are slowly building and almost permanent. Jurado et al. (2013) propose two new measures of uncertainty: the so-called common macroeconomic uncertainty factors based on a monthly data set containing financial and macroeconomic series and the so-called common firm-level uncertainty factors, which are extracted from firm-level profit growth rates. They identify uncertainty shocks by placing uncertainty second in the VAR, right after stock market returns. They conclude that uncertainty plays a larger role as driver of macroeconomic aggregates when measured using their broad-based estimates. Leduc and Liu (2013) estimate four-variate VAR models ordering first a direct measure of perceived uncertainty by consumers from the Michigan Survey. They conclude that the effects of uncertainty shocks on unemployment and inflation are similar to standard aggregate demand shocks.

To the best of our knowledge, there are only two attempts to jointly identify financial and uncertainty shocks. First, 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. So, although they assume financial markets respond contemporaneously to uncertainty shocks, both financial and uncertainty shocks are assumed to have a lagged effect on economic activity. They conclude that while uncertainty shocks have small and temporary effects on output and financial risk premia, financial shocks have more long-lasting effects on economic activity. Second, Gilchrist et al. (2013) explore the implications of alternative orderings of the uncertainty and financial disruptions proxies. They first assume that uncertainty shocks have an immediate impact on credit spreads and short-term interest rates, but they affect economic activity and prices with a lag. Then they reverse the ordering of the uncertainty proxy and credit spreads so they can explore the transmission mechanism of uncertainty shocks conditional on shocks to credit spreads. They conclude that the transmission of uncertainty shocks is sensitive to the whether the shocks are orthogonal to contemporaneous movements in credit spreads.

The remainder of the paper is organized as follows. Section 2 presents an overview of the uncertainty proxies; while section 3 describes our proxy for financial distress and provides an analysis of the statistical relationship between uncertainty and financial distress proxies.

Section 4 introduces the econometric methodology. Section 5 presents the results for our benchmark specification. Section 6 provides a robustness analysis and Section 7 concludes.

2. Measuring Economic Uncertainty

The recent financial crisis and consequent recession have raised concern about the role played by macroeconomic uncertainty in driving business cycle fluctuations. But there is no consensus among researchers on an objective measure of uncertainty, which has translated into a horse race for uncertainty proxies. In this section, we analyze the statistical properties of six proxies for macroeconomic uncertainty. We focus on proxies available at monthly frequencies.

The first three proxies are based on equity market information: realized volatility (RVOL), idiosyncratic volatility (IVOL), and the Chicago Board of Option Exchange VXO index of percentage implied volatility. RVOL is the monthly standard deviation of daily firm-level stock returns for all U.S. nonfinancial corporations with at least 1,250 trading days of data from the Center for Research in Security Prices (CRSP) data base. To avoid the influence of outliers in the sample, we eliminate all firm/day observations with a daily absolute return in excess of 50 percent. IVOL is the monthly counterpart of the quarterly series put forward by Gilchrist et al. (2013), which captures shocks to idiosyncratic uncertainty that are common to all firms. IVOL is computed using a three-step procedure. First, we remove the forecastable variation in daily excess returns using a four-factor model. Second, we compute the monthly firm-specific standard deviation of daily idiosyncratic returns. Third, we estimate an autoregressive model with firm and time fixed effects. IVOL corresponds to the sequence of time fixed effects.[2] The VXO index is based on a hypothetical at the money S&P100 option 30 days to expiration, as used by Bloom (2009). RVOL and IVOL are available from 1973 to 2012, while VXO is available from 1986 to 2012.

The fourth proxy for macroeconomic uncertainty, proposed by Bachmann et al. (2013), is a measure of forecast dispersion constructed using the Philadelphia Fed's Business Outlook Survey. This monthly survey of manufacturing firms contains qualitative information on the current state of firms' business conditions and expectations on future business conditions. From the survey, Bachmann et al. (2013) focus on two questions: *Q3: General Business Conditions: What is your evaluation of the level of general business activity six months from now versus* [current month]: *decrease, no change, increase?*; and *Q4: Company Business Indicators: Shipments six months from now versus* [current month]: *decrease, no change,*

[2]We refer to the appendix for further details on the construction of IVOL.

increase?. Their measure for time-varying business-level uncertainty (DISP hereafter) is the cross-sectional forecast dispersion for *Q3*, supplemented by the cross-sectional forecast dispersion for *Q4*. This series is available from 1973 to the end of 2011.

The fifth proxy, proposed by Baker et al. (2013), is an index of policy-related economic uncertainty (BBD hereafter) based on three components: *(i)* the frequency of newspaper references to policy-related economic uncertainty; *(ii)* the number and revenue impact of federal tax code provisions set to expire in future years; and *(iii)* the disagreement among professional forecasters on future government purchases and future inflation. The policy-related economic uncertainty index is available from 1985.

The last proxy we consider is the Scotti (2012)'s real-time uncertainty index (SRU hereafter), which compiles how uncertain agents are about real economic activity. Scotti (2012) estimates a dynamic factor model on actual releases of macroeconomic variables to construct monthly business conditions indexes and compute forecasting weights. Surprises are defined as the difference between actual releases and Bloomberg expectations on the variable. The SRU index is computed as the square root of the weighted average of the squared surprises, where the time-varying weight are the forecasting weights extracted in the dynamic factor model estimation. This index is only available from 1991.

In Table B.1, we report the coefficient of variation and autocorrelation coefficients for the uncertainty proxies. We compute these moments using the common sample 1986:M1 to 2011:M12, with the exception of SRU for which the sample starts in 1991:M1. The coefficient of variation varies substantially across uncertainty proxies ranging from 0.66 for RVOL to 0.09 for DISP. Similarly, we find heterogeneity in the degree of autocorrelation, which is higher for BBD and VXO, somewhat lower for RVOL, DISP, and IVOL, and low for SRU.

The heterogeneity in variability and persistence of uncertainty proxies is also present in their degree of correlation, which we report in Table B.2. While the three equity market based measures of uncertainty are highly correlated, their correlation with the other proxies is relatively weak. This low correlation is also present among the non-stock market based measures. In particular, DISP is not strongly correlated with any of the other uncertainty proxies. The weakness of the relationship between forecast dispersion and economic uncertainty has been highlighted earlier in the literature. For example, D'Amico and Orphanides (2008) find that disagreement about the mean inflation forecast in the Survey of Professional Forecasters is not a good proxy for inflation uncertainty. Instead, they find that inflation uncertainty is more correlated with the mean inflation forecast than with the dispersion of individual forecasts. Orlik and Veldkamp (2013) show that forecast dispersion and macroe-

conomic uncertainty can coincide but only under two stringent conditions for forecast errors: they do not have a common component and they have the same variance.

Despite the relatively low correlation, uncertainty proxies may still be driven by some underlying common factors. To test this hypothesis, we extract the common variation in uncertainty proxies using principal components analysis, which uses the deviations from the mean cross-product matrix of the variables. The first principal component accounts for as much of the variability in the data as possible and each of the succeeding principal components account for as much of the remaining variability as possible. We perform this analysis on all uncertainty proxies but SRU so we can rely on a larger common sample: 1986:M1-2011:M12. We summarize the results in Table B.3. The first column in the upper panel states the total variance accounted for by each of the principal components, the second column reports the cumulative variance, and the third column states the proportion of the total variance accounted for by the corresponding principal component. The first component accounts for 56% of the total variance in the system, the second component for 20%, and the third component for 15%. We report loadings for the first three components in the lower panel of Table B.3. The loading coefficients for the first component are in the 0.4-0.6 range for all variables but DISP, whose loading is only 0.1. Instead, DISP loads on the second component, while the loadings for all of the other variables are almost negligible or negative. Similarly, BBD, which has the second smallest loading on the first principal component, loads mostly on the third component. These results highlight that DISP, equity based measured, and BBD seem to be measuring different uncertainty processes.

Finally, we analyze the business cycle properties of the uncertainty measures by computing the cross-correlogram between the uncertainty measures and the real-time business conditions index developed by Aruoba et al. (2009). As shown in Table B.4, all uncertainty measures are negatively correlated with the business conditions index at all leads and lags. The cross-correlations are of similar magnitude for all variables but DISP, which displays lower correlations.

Summing up, there is a wide array of competing uncertainty proxies available in the literature. All of these measures have distinct characteristics but, as suggested by the principal component analysis, they seem to capture some common underlying element. The exception to the rule is the forecast dispersion measure, which seems to be accounting for something different than the other uncertainty proxies.

3. Measuring Financial Distress

Gilchrist and Zakrajšek (2012) construct a corporate bond credit spread index – the GZ

credit spread – using monthly data on prices of individual corporate bonds traded in the secondary market. They decompose the GZ spread 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 – the so-called external finance premium (EBP hereafter). This residual component is, therefore, computed controlling for the distance to default and, moreover, it is purged of fluctuations in volatility. Gilchrist and Zakrajšek (2012) provide evidence suggesting a link between the residual component of the GZ credit spread and the risk bearing capacity of the financial intermediation sector. Thus, we argue that shocks to EBP plausibly reflect disruptions in the credit intermediation process and, hence, are a good proxy for financial distress.

During the 2007-2009 recession, practitioners relied on credit spreads as proxies for financial distress since movements in credit spreads can provide early warnings of economic downturns. There is a large literature establishing the predictive content of credit spreads for economic activity. Recently, Phillipon (2009) develops a theoretical framework in which the predictive content of corporate bond credit spreads for economic activity – absent any financial rigidity – is larger than stock market asset prices. Thus, the bond market is more accurate than the stock market in signaling a decline in economic activity prior to a recession since rising corporate bond credit spreads represent a decline in the expected present value of cash flows. In an environment with financial frictions, rising corporate bond credit spreads may reflect disruptions in the supply of credit due to, as pointed out by Bernanke et al. (1999), a deterioration of corporate balance sheets or of the health of financial intermediaries. In this environment, a reduction in the supply of credit widens credit spreads so that debt financing collapses and, consequently, investment and production. The GZ credit spread index is a highly informative financial indicator whose predictive ability exceeds that of default-risk indicators such as the Baa–Aaa corporate bond credit spread.

From a no-arbitrage standpoint, corporate bond credit spreads are driven by default risk and changes in the recovery rate. However, Collin-Dufresne et al. (2001) document the so-called credit spread puzzle: these two factors can only account for 25% of the observed variation in corporate bond credit spreads. Given the historically low contribution of fluctuations in default risk to credit spreads, the decomposition of the GZ credit spread implies that a large proportion of the variation in spreads should be accounted for by movements in the residual component. Gilchrist and Zakrajšek (2012) conclude that, in fact, most of the predictive content of the GZ corporate bond credit spread index is due to fluctuations in EBP.

Figure add–ref shows the EBP and the NBER dated recessions. All economic downturns, with the exception of the 1990-1991 recession, are characterized by a significant increase of the excess bond premium immediately prior to or during the recession. The two long expansions of the 1990s and 2000s are characterized by historically low levels of the EBP, suggesting that improvements in the conditions of access to credit did have an impact on the average level of EBP. The countercyclical nature of the EBP is also clear from Table B.5 where we report the cross-correlogram between the residual component and the business condition index by Aruoba et al. (2009).

3.1. Relationship between EBP and Uncertainty Measures

As the goal of the paper is to identify jointly financial and uncertainty shocks, in this section we analyze the statistical relationship between our measure of financial distress (EBP) and the uncertainty proxies. First, we explore their correlation structure. Second, we run a battery of Granger-causality tests. Finally, we test for the statistically significance of uncertainty (EBP) in forecasting the EBP (uncertainty) conditional on either the state of the economy or the monetary policy stance.

We report in Table B.6 the correlation structure between the EBP and the uncertainty proxies. Equity based measures of uncertainty display the highest correlation with the EBP, in particular VXO (0.58) and RVOL (0.57). The BBD and SRU proxies are less correlated, while DISP displays the lowest correlation (0.26). Thus, there is a positive correlation between financial distress and economic uncertainty, but such correlation is not very large.

The correlation analysis presented above focuses on the contemporaneous relationship between financial distress and uncertainty. We are also interested in exploring the role played by uncertainty in forecasting financial distress and vice versa. To do so, we perform Granger (1969) causality tests based on the following regression[3]

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

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 B.7. From the upper panel in Table B.7, we conclude that

[3]We perform optimal lag selection using a two-step procedure. We first select the optimal lag length in the restricted model, that is, we first choose h. Conditional on h, we select the optimal lag length in the unrestricted model, k.

only the RVOL and the VXO index Granger-cause the EBP. Conversely, the EBP Granger-causes all uncertainty measures but DISP, as reported in the lower panel in Table B.7. Therefore, while the EBP incorporates information regarding the evolution of uncertainty in the economy, uncertainty proxies seem to be less essential in predicting the external finance premium.

We then ask whether these asymmetric results regarding the direction of Granger-causality are an artifact of omitted information. To address this issue, we incorporate in the regression analysis either the state of the economy through the Aruoba et al. (2009) business conditions index or the state of monetary policy through the federal funds rate. In particular, we replace regression model in equation 1 by

$$y_t = \alpha + \sum_{i=1}^{h} \beta_i y_{t-i} + \sum_{j=1}^{k} \gamma_j x_{t-j} + \sum_{l=1}^{m} \gamma_j z_{t-l} + \epsilon_{y,t}, \ t = 1, \ldots, T, \tag{2}$$

where z_t stands for the business conditions index or the federal funds rate. The Granger test of interest is still an F-test of $H_0 : \gamma_j = 0, \forall j$. Table B.8 reports the Granger tests conditional on the Aruoba et al. (2009) business conditions index and table B.9 compiles the results conditional on the federal funds rate. As reported in the simple case, only RVOL and VXO Granger-cause the excess bond premium both conditional on the state of the macroeconomy and the monetary policy stance. IVOL also Granger-causes EBP when we include in the regression analysis the lagged federal funds rate. The statistical significance of the financial distress proxy in predicting uncertainty is compromised when we include the business condition index for IVOL, BBD, and SRU (in addition to DISP). When the regression conditions on the federal funds rate, only BBD (in addition to DISP) is not Granger-caused by the excess bond premium.

The statistical analysis presented in this section regarding the relationship between our proxy for financial distress and a wide array of uncertainty measures allow us to conclude that the best framework to further explore such relationship is a vector autoregressive model that includes macroeconomic and financial variables.

4. Empirical Methodology

The relationship between uncertainty proxies and financial market disruptions documented in the previous section establishes that periods of financial market distress are generally associated with a significant increase in economic uncertainty and spikes in uncertainty are frequently accompanied by disruptions in financial markets. Thus, distinguishing between financial and uncertainty shocks within a standard VAR framework poses a set of challenges.

On the one hand, uncertainty and financial distress proxies are "fast-moving" variables, which makes it difficult to impose plausible zero contemporaneous restrictions to identify uncertainty and financial shocks. Gilchrist et al. (2013) explore the implications of alternative orderings of the uncertainty and financial disruptions proxies. They first assume that uncertainty shocks have an immediate impact on credit spreads and short-term interest rates, but they affect economic activity and prices with a lag. Then they reverse the ordering of the uncertainty proxy and credit spreads so they can explore the transmission mechanism of uncertainty shocks conditional on shocks to credit spreads. They conclude that the transmission of uncertainty shocks is sensitive to whether the shocks are orthogonal to contemporaneous movements in credit spreads.

On the other hand, it is difficult to impose sign restrictions on the impulse response functions since financial and uncertainty shocks have the same qualitative effects on prices and quantities. Leduc and Liu (2013) show that uncertainty shocks raise unemployment and lower inflation and nominal interest rates. Gilchrist and Zakrajšek (2012) conclude that an adverse financial shock generates a recession in the real side of the economy, while reducing prices and nominal interest rates. Moreover, Gilchrist et al. (2013) provide evidence on uncertainty and adverse financial shocks reducing economic activity and raising credit spreads.

We propose to identify financial and uncertainty shocks using an optimization based procedure in the spirit of Uhlig (2005). Under our optimization based approach, a structural shock is identified using the criterion that such shock optimizes the response of a target variable over a given horizon. Thus, rather than simultaneously identifying the two sources of business cycle fluctuations of our interest, we implement the optimization criterion sequentially subject to an orthogonality condition.

Let us consider the reduced-form VAR model

$$X_t = \mu + B(L)X_{t-1} + u_t, \tag{3}$$

where X_t is a vector of m endogenous variables, μ is a constant, $B(L)$ is a lag polynomial of order L, and u_t is a vector of one-step-ahead prediction errors with zero mean and positive definite covariance matrix $\Sigma_u = [\sigma_{ij}]$. The reduced-form disturbances u_t will, in general, be correlated with each other and consequently do not have any economic interpretation. It is thus necessary to model the contemporaneous relation between the elements of u_t to identify structural shocks e_t with an economic interpretation:

$$Au_t = e_t, \tag{4}$$

where $A = [a_{ij}]$ is a matrix holding the structural coefficients and e_t have zero mean and are normalized to have unitary variance, i.e. $\Sigma_e = I$. Alternatively, we can write equation (4) as

$$u_t = Fe_t, \tag{5}$$

where $F = A^{-1}$. Columns of matrix F, denoted by $f^{(j)}$, are known as impulse vectors (Uhlig, 2005), with $f_i^{(j)}$ giving the contemporaneous effect on variable i to shock j of size one standard deviation. We restrict attention to the class of just-identified SVAR models for which

$$FF' = \Sigma_u, \tag{6}$$

As in Mountford and Uhlig (2009), let us define an impulse matrix of rank n as a $n \times m$ sub-matrix of some $m \times m$ matrix F such that (6) holds. As shown in Uhlig (2005), SVAR identification does not have to necessarily identify all m structural shocks, but it can only identify a subset of n shocks. In this paper, we identify two fundamental shocks, $e^{(1)}$ and $e^{(2)}$, corresponding to the impulse matrix $\left[f^{(1)}, f^{(2)}\right]$.

To this end, note that any impulse matrix F can be written as the product of the lower triangular Cholesky factor $\tilde{F}$ of Σ_u with an $n \times m$ matrix $Q = \left[q^{(1)}, q^{(2)}\right]$ of orthonormal rows, ie $QQ' = I$. As shown in Mountford and Uhlig (2009), the impulse response for the impulse vector $f(i)$ can be written as a linear combination of the responses to the Cholesky decomposition of Σ. Define $r_{ji}(k)$ as the impulse response of variable j at horizon k to the ith column of $\tilde{F}$, and the m-dimensional column vector $r_i(k)$ as $[r_{1i}(k), ..., r_{mi}(k)]$. Then the m-dimensional impulse response $r_f(k)$ at horizon k to the impulse vector $f^{(s)}$ is given by

$$r_f(k) = \sum_{i=1}^{m} q_i r_i(k) \tag{7}$$

where q_i is the ith entry of $q = q^{(s)}$. Define J as the set of variables that we want to restrict, and K the number of periods we want to restrict them for. To identify the first shock we solve

$$f^{(1)} = \underset{f=\tilde{F}q}{\operatorname{argmin}}\, \Omega(f), \tag{8}$$

where

$$\Omega(f) = \sum_{j \in J} \sum_{k=0}^{K} \frac{r_{jf}(k)}{s_j} \tag{9}$$

where s_j is the standard deviation of the j-th variable.

To identify the second shock, we replace the minimization problem shown above with

$$f^{(2)} = \underset{f=\tilde{F}q, q'q^{(1)}=0}{\operatorname{argmin}} \Omega(f), \tag{10}$$

That is, we additionally impose orthogonality between the first and the second shock.

Our optimization based procedure does not impose sign restrictions on the elements of $r_{jf}(k)$ via inequality constraints as in Mountford and Uhlig (2009). We focus on searching for shocks that increase the restricted variables for K periods, which implies that we maximize the sum of positive responses of variables J to shocks 1 and 2. In our application, all restricted responses are positive so none of the draws would actually violate additional inequality constraints.

We maximize the response of variables J scaled by their standard deviation while Kurmann and Otrok (2013) optimize the contribution of shocks 1 and 2 to the forecast error variance (FEV) of variables J. Shocks that maximize the contribution to the FEV could be such that the EBP (or uncertainty proxy) increase in the short run, while decreasing in the long run (an initial large response followed by a massive undershooting). However, we are interested in shocks that generate a persistent increase in financial disruptions and uncertainty. In many practical applications, VAR responses to a given shock are fairly persistent so the two optimization approaches to identification lead to very similar results.

Given the sequential nature of our identification strategy, we explore two identification schemes: baseline identification and alternative identification. In the baseline identification, we first search for a shock that maximizes the response of the EBP over a three-month horizon. This shock singles out the most important driver of our financial distress proxy, which is, by construction, orthogonal to the state of the economy and purged of volatility. Thus, we interpret this shock as a financial shock. In a second step, we search for an orthogonal shock that maximizes the response of the uncertainty proxy over a three-month horizon – we label this an uncertainty shock. Therefore, in the baseline identification, uncertainty shocks are conditional to financial shocks, which limits the transmission of uncertainty shocks through the financial channel captured by EBP.

In the alternative identification, we revert the ordering so that we first search for the most important driver of swings in economic uncertainty and then search for an orthogonal shock that maximizes the response of the EBP over the three-month horizon. In this identification, uncertainty shocks are allowed to explain fluctuations in EBP without conditioning on

financial shocks. We argue that, under the alternative identification strategy, the financial channel in the transmission mechanism of uncertainty shocks is fully open.

4.1. Data and Specification

Besides the EBP and an uncertainty proxy, we incorporate in the analysis other financial and nominal fast-moving variables. In particular, we consider the monthly averages of the federal funds rate, the 10-year Treasury yield, and stock market returns. Our measure of stock market returns is based on daily firm-level stock returns data for all U.S. nonfinancial corporations with at least 1,250 trading days of data from CRSP[4].

In addition to the fast-moving variables, our VAR model also contains slow-moving real and nominal indicators. We include the real counterpart of the industrial production index provided by the Board of Governors, the employment in the nonfarm business sector provided by the Bureau of Labor Statistics, the real counterpart of personal consumption expenditures (PCE) provided by the Bureau of Economic Analysis, and the PCE implicit price deflator. We remove a linear trend from the slow-moving variables.

Our benchmark specification is a nine-variate VAR(6) model containing all the variables stated above. Our baseline uncertainty measure is the RVOL described in section 2. The estimation sample is 1973:M1-2012:M12. We estimate the VAR model using Bayesian techniques. In particular, we assume a Minnesota prior à la Doan et al. (1984) with hyperparameters set as in Fuentes-Albero and Melosi (2013) by optimizing the model fit over a pre-sample of size 24 months. We generate 50,000 draws from the posterior[5] and discard the first 10,000 when implementing the identification strategy.

In section 5.1, we explore the sensitivity of our results to some data choices. First, we replace personal consumption expenditures with its components: durable goods and nondurable goods. Second, we re-estimate the benchmark specification adding core lending – loans to business and households – as a summary statistic for credit markets. This data series is available only from 1985:M6.

5. Benchmark Results

Our results indicate that a one standard deviation adverse shock to the EBP leads to a persistent decline in economic activity and stock market returns. Macroeconomic implications of financial shocks are similar across identification schemes. This robust feature of

[4]We use the same data as to construct RVOL and IVOL.

[5]The model is non-stationary for some posterior draws 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.

financial shocks does not extend to uncertainty shocks. Uncertainty shocks have a significant macroeconomic impact only under the alternative identification, where they elicit a significant and persistent response of the EBP. In the baseline identification, the impact of uncertainty shocks is significantly attenuated and has no effect on financial conditions. Thus we argue that the financial channel is key in the transmission mechanism of uncertainty shocks, while the role played by the uncertainty channel in the transmission mechanism of financial shocks is minimal.

We report the impulse responses to a financial shock under the baseline identification in Figure C.1. The solid line represents the median response and the band corresponds to the 95% confidence interval. An unanticipated increase of one standard deviation in the EBP – about 25 basis points – generates sizable lagged adverse macroeconomic effects. The responses upon impact for all variables but RVOL and stock market returns are not significantly different from zero. Thus, we get zero responses upon impact as a result and not as an assumption of the identification strategy. An adverse financial shock generates a large and long-lasting recession. In particular, the 25 basis points increase in the EBP translates into a collapse of the level of industrial production that bottoms out about 1 percentage points below trend 18 months after the shock. Employment bottoms out about 0.45 percentage points below trend 24 months after the financial shock. The response of PCE is steadily declining during the 36 months reported in the graph. Thus three years after the shock, consumption expenditures are still 0.3 percentage points below trend. It is noteworthy that the recovery in the real side of the economy is very slow and it is far from being over even 36 months after the shock. Financial shocks generate an immediate collapse of the stock market of about 1.25 percentage points, which worsens over the following year. The recovery in the stock market is also sluggish so that 36 months after the shock, stock market returns are about 2 percentage points below trend. Financial shocks induce persistent deflationary pressures and a reduction in long-run yields. Finally, the financial shock leads to a modest but persistent increase in uncertainty.

Under the alternative identification, the effects of financial shocks are qualitatively similar to the ones described above as shown in Figure C.2. The most remarkable difference is the response of the uncertainty proxy. While RVOL increases under the baseline identification, the response upon impact in the alternative identification is negative. Given that, despite of the response of the uncertainty proxy, the macroeconomic implications of financial shocks are qualitatively and quantitatively similar across identifications, we argue that the uncertainty channel plays a minimal role, if any, in the transmission of financial shocks.

We analyze the relative importance of financial shocks in driving economic activity in

Figure C.3. The solid line and the band correspond to the median contribution of financial shocks to the FEV and the 95% confidence interval in the baseline identification. The dotted line represents the median contribution of financial shocks under the alternative identification. We conclude that financial shocks are relevant drivers of business cycle fluctuations in real variables and stock market returns. At the 36-month horizon, financial shocks account for 20-30% of the forecast error variance (FEV hereafter) in the industrial production index, 15-30% of the variability in employment, 15-20% of the FEV in PCE, and 30-40% of the volatility in stock market returns. However, the role played by financial shocks in driving nominal variables is significantly smaller. In particular, the contribution of financial shocks to the FEV of nominal variables is in the ballpark of 8%. The stability in the contribution to the FEV across identification schemes highlights again the small role played by the uncertainty channel in the transmission of financial shocks in the U.S. economy. Financial shocks do account for 20% of the variability in RVOL under the baseline identification, but their role is not significant under the alternative identification.

We analyze the transmission of uncertainty shocks identified using the alternative identification scheme in Figure C.4. A one standard deviation increase in RVOL translates into an immediate moderate widening of credit spreads and a 2 percentage points collapse in the stock market. Uncertainty shocks trigger a slowly-building and persistent recession followed by a slow recovery. These shocks are also deflationary and reduce long-run interest rates. However, the response of the 10-year Treasury yield bottoms out 6 months after the shock instead of engaging in a persistent decline as in response to financial shocks. The adverse effects of uncertainty shocks are qualitatively similar to those of financial shocks.

The transmission mechanism of uncertainty shocks is not robust to altering the sequential ordering in the identification scheme. Figure C.5 reports the transmission of uncertainty shocks under the baseline identification. Given that most of the variation in the EBP is captured by the financial shock identified in the first step of the identification scheme, we argue that the financial channel in the transmission of uncertainty shocks is impaired in this scenario. In this case, the impact of uncertainty shocks is significantly attenuated. In particular, only the response of stock market returns is significantly different from zero. Therefore, the baseline identification singles out spikes in uncertainty generating a slowdown in the stock market that does not transmit to the real side of the economy.

Figure C.6 provides the median contribution to the FEV of uncertainty shocks. Under the alternative identification, uncertainty shocks account for 8-12% of the FEV in real variables and 20% of that in the EBP. The relative role played by uncertainty shocks in driving these variables is not significantly different from zero under the baseline identification. Uncertainty

shocks account for 5-15% of the variability in stock market returns at the 36-month horizon. At the 3-6 month horizon, the contribution to the FEV in stock market returns peaks at about 30% under the alternative identification and 18% under the baseline identification. Comparing Figure C.3 and Figure C.6, we conclude that while uncertainty shocks are key in accounting for stock market variation at short horizons, financial shocks are key at longer horizons.

We also explore the role of both uncertainty and financial shocks in driving business cycle fluctuations by means of a historical variance decomposition in Figure C.7. Financial and uncertainty shocks account for about 50% of the drop in industrial production during the mid-1970s recession, the dot-com burst in the early 2000s, and the Great Recession. Financial shocks are relatively more important than uncertainty shocks during these episodes. These two types of shocks account for almost all the fluctuations in the stock market since the early 2000s, while their role in equity markets is more models in earlier periods.

Summing up, through the lenses of the baseline identification, our results indicate that failing to control for financial shocks may overstate the macroeconomic effects of uncertainty shocks. The fact that uncertainty increases upon impact in response to a financial shock suggests that swings in uncertainty are influenced importantly by changes in financial conditions. Through the lenses of the alternative identification scheme, our findings indicate that uncertainty shocks have sizable effects on the real economy, especially in circumstances when they induce a concomitant deterioration in financial conditions.

5.1. Discussion

Our results assess an important role to the financial channel in the transmission of uncertainty shocks. In order to investigate further the relative role played by the EBP in the propagation of uncertainty shocks, we propose a constrained optimization based approach to identification. In particular, we use the alternative identification explained above subject to a zero response upon impact for the EBP. Thus, our constrained optimization identification scheme searches for the shock that maximizes the response of RVOL over a three-month horizon and does not move the EBP upon impact. The small twist in the alternative identification scheme allows us to study the effects of closing completely the financial channel in the transmission of uncertainty shocks. The solid line in Figure C.8 represents the median response to an uncertainty shock under the alternative identification and the dotted line is the median response under the constrained alternative identification. Closing the financial channel upon impact is enough to compress the macroeconomic effects of uncertainty shocks in by a half.

We investigate further the interpretation of shocks to the EBP as exogenous disruptions to the credit-intermediation process by extending the VAR model to incorporate core loans – loans to business and households. We report the responses of core loans to financial and uncertainty shocks in Figure C.9. The response of core loans to financial shocks is not significant until nine months after the shock when core loans initiate a steady decline so that at the 36-month horizon, credit is 1 percentage points below trend. The response of core loans to uncertainty shocks under both identification schemes is not significantly different from zero at almost any horizon. Therefore, we conclude that while uncertainty shocks do not impair the functioning of the credit-intermediation process, financial shocks always depress credit availability.

We analyze the transmission of financial and uncertainty shocks across consumption categories in Figure C.10. The solid line corresponds to the IRF for total consumption, the dashed line to the response for nondurable consumption and services, and the dotted line is the IRF for non-durable consumption. The responses to both types of shocks for PCE and PCE nondurables and services are almost identical. After a 25 basis point increase in the EBP, durable consumption declines upon impact 0.2-0.3 percentage points. The initial contraction in durable consumption is followed by a sharp decline that bottoms out about 0.5 percentage points below trend 12 months after the shock. This effect in durable consumption seems to be permanent-like since there is no recovery in the following 24 months. Uncertainty shocks identified using the baseline identification have the same qualitative effects on durable consumption than financial shocks.

6. Robustness

In this section, we perform several robustness exercises. We study the sensitivity of our results to the sample under analysis, alternative uncertainty proxies, and changes in the horizon used in the criterion function. We focus our discussion on the response of the industrial production index but the results carry over the other real variables under analysis. Figure **??** and Figure C.13 report the responses to a financial shock under the baseline and alternative identifications respectively for the uncertainty proxies reviewed in Section 2. While the VAR models including RVOL, IVOL, or DISP are estimated using the 1973-2012 database, the data sample for the VAR models including BBD and VXO starts in the Great Moderation era. Thus, we can analyze both the sensitivity of our results to uncertainty proxies and to the data sample. The responses to financial shocks are qualitatively similar for all uncertainty proxies. But it is remarkable that excluding the 1970s translates into a relatively stronger effect of financial shocks in real economic activity and stock market

returns. In the baseline identification, the through of stock market returns is 40% larger when considering the most recent sample and that of the industrial production index is 20% larger.

Figure C.14 and Figure C.15 provide the responses to an uncertainty shock under the alternative and baseline identifications respectively. The picture is less straightforward than for financial shocks, but we can still argue that under the alternative identification, qualitatively, the effects of uncertainty shocks in real variables and stock market returns are robust to the uncertainty proxy included in the VAR model. The effects of uncertainty shocks in nominal variables are less robust to the data choice.

7. Conclusions

References

Arias, J., Rubio-Ramirez, J., Waggoner, D., 2013. Inference based on svars identified with sign and zero restrictions, working Paper, Dept. of Economics, Duke University.

Aruoba, S. B., Diebold, F. X., Scotti, C., 2009. Real-time measurement of business conditions. Journal of Business & Economic Studies 27 (4), 417–427.

Bachmann, R., Elstner, S., Sims, E., 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., 2013. Measuring economic policy uncertainty, manuscript, Stanford University.

Bernanke, B. S., Gertler, M., Gilchrist, S., 1999. The financial accelerator in a quantitative business cycle framework. In: Taylor, J., Woodford, M. (Eds.), The Handbook of Macroeconomics. Elsevier Science B.V., Amsterdam, The Netherlands, pp. 1341–1393.

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

Boivin, J., Giannoni, M. P., Stevanović, D., 2013. Dynamic effects of credit shocks in a data-rich environment, federal Reserve Bank of New York, Staff Report No. 615.

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

Collin-Dufresne, P., Goldstein, R. S., Martin, J. S., 2001. The determinants of credit spread changes. The Journal of Finance 56 (6), 2177–2207.

D'Amico, S., Orphanides, A., 2008. Uncertainty and disagreement in economic forecasting, mimeo, Federal Reserve Board.

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

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., 2013. Methods for computing marginal data densities from the gibbs output. Journal of Econometrics 175 (2), 132–141, august.

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

Gilchrist, S., Sim, J. W., Zakrajšek, E., 2013. 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.

Jurado, K., Ludvigson, S. C., Ng, S., 2013. Measuring uncertainty, mimeo.

Kurmann, A., Otrok, C., 2013. News shocks and the slope of the term structure of the interest rates. American Economic Review 103 (6), 2612–32.

Leduc, S., Liu, Z., 2013. Uncertainty shocks are aggregate demand shocks, federal Reserve Bank of San Francisco Working Paper 2012-10.

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

Mountford, A., Uhlig, H., 2009. What are the effects of fiscal policy shocks? Journal of Applied Econometrics 24 (6), 960–992.

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

Orlik, A., Veldkamp, L., 2013. Understanding uncertainty shocks and the role of black swans, mimeo, Federal Reserve Board.

Phillipon, T., 2009. The bon market's q. Quarterly Journal of Economics 124 (3), 1011–56.

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

Prieto, E., Eickmeier, S., Marcellino, M., 2013. Time variation in macro-financial linkages, mimeo.

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.

Scotti, C., 2012. Surprise and uncertainty indexes: Real-time aggregation of real-activity macro surprises, mimeo, Federal Reserve Board.

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

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

Uhlig, H., 2005. What are the effects of monetary policy on output? results from an agnostic identification procedure. Journal of Monetary Economics 52, 381–419.

Appendix A. Data

Idiosyncratic volatility (IVOL) is constructed using the three-step procedure proposed by Gilchrist et al. (2013)

1. We remove the forecastable variation in daily excess returns using a linear four-factor model. In particular, we augment the standard Fama and French (1992) three-factor model with the moment risk factor proposed by Carhart (1997).

$$\left(R_{it_d} - r^f_{t_d}\right) = \alpha_i + \beta_i' \mathbf{f}_{t_d} + u_{it_d} \tag{A.1}$$

   where $i = 1$ indexes firms; $d = 1, \ldots, D$ indexes trading days in month t; R_{it_d} stands for the total daily return of firm i; $r^f_{t_d}$ is the risk-free rate; and $\mathbf{f}_{t_d}$ is the vector of factors.

2. We compute the monthly firm-specific standard deviation of daily idiosyncratic returns

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

   where u_{it_d} is the OLS residual from (A.1)and $\bar{u}_{it_d}$ is the sample mean of daily idiosyncratic returns in month t.

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

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

   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).

Appendix B. Tables

Table B.1: Summary statistics

	Coefficient of variation	AR(1)	AR(2)	AR(3)	AR(10)
RVOL	0.66	0.71	0.57	0.46	0.22
IVOL	0.28	0.56	0.44	0.34	0.26
DISP	0.09	0.70	0.64	0.50	0.22
BBD	0.30	0.83	0.71	0.64	0.49
VXO	0.40	0.83	0.68	0.58	0.34
SRU*	0.39	0.54	0.31	0.22	-0.04

Notes: The sample for all variables but SRU ranges from 1986:M1 to 2011:M12. The sample for the SRU starts in 1991:M1

Table B.2: Correlation coefficients

	RVOL	IVOL	DISP	BBD	VXO	SRU
RVOL	1	0.75	0.12	0.48	0.84	0.38
IVOL		1	0.04	0.30	0.59	0.27
DISP			1	-0.01	0.19	0.14
BBD				1	0.49	0.24
VXO					1	0.33
SRU*						1

Notes: The sample for all variables but SRU ranges from 1986:M1 to 2011:M12. The sample for SRU starts in 1991:M1

Table B.3: Principal components analysis

Eigenvalues			
PC	Value	Cumulative Value	Proportion
1	2.78	2.78	0.56
2	1.01	3.79	0.20
3	0.73	4.52	0.15
4	0.36	4.88	0.07
5	0.12	5.00	0.02
Eigenvectors–Loadings			
Variable	PC 1	PC 2	PC 3
RVOL	0.57	-0.02	-0.16
IVOL	0.48	-0.09	-0.51
DISP	0.10	0.96	0.16
BBD	0.38	-0.24	0.83
VXO	0.54	0.08	0.01

Notes: The sample ranges from 1986:M1 to 2011:M12.

Table B.4: Correlation coefficients between uncertainty and economic activity

	$t=-3$	$t=-2$	$t=-1$	$t=0$	$t=1$	$t=2$	$t=3$
RVOL	-0.41	-0.45	-0.47	-0.47	-0.50	-0.51	-0.48
IVOL	-0.24	-0.26	-0.30	-0.30	-0.32	-0.35	-0.34
DISP	-0.06	-0.13	-0.18	-0.23	-0.24	-0.25	-0.21
BBD	-0.38	-0.40	-0.42	-0.41	-0.39	-0.37	-0.31
VXO	-0.32	-0.37	-0.39	-0.38	-0.40	-0.42	-0.39
SRU*	-0.44	-0.50	-0.52	-0.47	-0.42	-0.41	-0.37

Notes: The sample for all variables but the SRU ranges from 1986:M1 to 2011:M12. The sample for the SRU starts in 1991:M1

Table B.5: Correlation coefficients between EBP and economic activity

	$t=-3$	$t=-2$	$t=-1$	$t=0$	$t=1$	$t=2$	$t=3$
1986:M1–2011:M12	-0.57	-0.63	-0.67	-0.66	-0.66	-0.65	-0.61
1973:M1–2012:M12	-0.46	-0.50	-0.52	-0.52	-0.51	-0.51	-0.48

Table B.6: Correlation coefficients between EBP and uncertainty

	RVOL	IVOL	DISP	BBD	VXO	SRU*
EBP	0.57	0.37	0.26	0.42	0.58	0.39

Notes: The sample for all variables but SRU ranges from 1986:M1 to 2011:M12. The sample for SRU starts in 1991:M1

Table B.7: Bivariate 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	BBD	VXO	SRU*
k	1	1	1	1	2	1
$\sum_{j=1}^{k} \gamma_k$	0.0844	0.0334	0.0168	-0.0022	0.0349	0.0189
95% CI	[0.0348, 0.1340]	[-0.0190, 0.0858]	[-0.0165, 0.0502]	[-0.0593, 0.0550]	[-0.2086, 0.2784]	[-0.0341, 0.0719]
p-value for F-test	0.0008	0.2111	0.3208	0.9409	0.0001	0.4834
$\sigma_t = \alpha + \sum_{i=1}^{h} \beta_i \sigma_{t-i} + \sum_{j=1}^{k} \gamma_j EBP_{t-j} + \epsilon_t$						
σ	RVOL	IVOL	DISP	BBD	VXO	SRU*
h	2	2	2	4	1	1
k	1	1	1	1	1	1
$\sum_{j=1}^{k} \gamma_k$	0.2128	0.0742	-0.0122	0.0482	0.1520	0.2213
95% CI	[0.0599, 0.3657]	[0.0038, 0.1444]	[-0.0629, 0.0386]	[-0.0094, 0.1059]	[0.0590, 0.2450]	[0.0575, 0.3852]
p-value for F-test	0.0065	0.0388	0.6384	0.1007	0.0013	0.0078

Notes: The Granger tests for the pairs (EBP, RVOL) and (EBP, IVOL) are conducted with data from 1973:M1 to 2012:M12; for (EBP, DISP) from 1973:M1 to 2011:M12; for (EBP, BBD) from 1985:M1 to 2012:M12; for (EBP, VXO) from 1986:M1 to 2012:M12; and for (EBP, SRU) from 1991:M1 to 2012:M12. The linear regression models are estimated on standardized data using HAC-robust variance estimates. A test that σ_t does not Granger-cause EBP_t is an F-test of $H_0 : \gamma_j = 0, \forall j$.

Table B.8: Multivariate Granger tests: conditioning on economic activity

$EBP_t = \alpha + \sum_{i=1}^{2} \beta_i EBP_{t-i} + \sum_{j=1}^{k} \gamma_j \sigma_{t-j} + \sum_{l=1}^{m} \phi_l EA_{t-l} + \epsilon_t$						
σ	RVOL	IVOL	DISP	BBD	VXO	SRU
k	1	1	1	1	2	1
m	1	2	1	3	3	2
$\sum_{j=1}^{k} \gamma_k$	0.0763	0.0299	-0.0018	-0.0104	0.0372	0.0219
95% CI	[0.0282, 0.1242]	[-0.0210, 0.0806]	[-0.0358, 0.0322]	[-0.0701, 0.0493]	[-0.2201, 0.2944]	[-0.0443, 0.0881]
p-value for F-test	0.0019	0.2485	0.9159	0.7324	0.0004	0.5148
$\sigma_t = \alpha + \sum_{i=1}^{h} \beta_i \sigma_{t-i} + \sum_{j=1}^{k} \gamma_j EBP_{t-j} + \sum_{l=1}^{m} \phi_l EA_{t-l} + \epsilon_t$						
σ	RVOL	IVOL	DISP	BBD	VXO	SRU
h	2	2	2	4	1	1
k	1	1	1	1	1	1
m	1	1	1	1	1	1
$\sum_{j=1}^{k} \gamma_k$	0.2007	0.0752	-0.0018	0.0230	0.1391	0.0015
95% CI	[0.0618, 0.3397]	[-0.0110, 0.1615]	[-0.0358, 0.0322]	[-0.0558, 0.1018]	[0.0146, 0.2635]	[-0.1497, 0.1527]
p-value for F-test	0.0047	0.0872	0.7054	0.5664	0.0286	0.9848

Notes: The sample for all variables but SRU ranges from 1986:M1 to 2011:M12. The sample for SRU starts in 1991:M1.The linear regression models are estimated on standardized data using HAC-robust variance estimates. A test that σ_t does not Granger-cause EBP_t is an F-test of $H_0 : \gamma_j = 0, \forall j$.

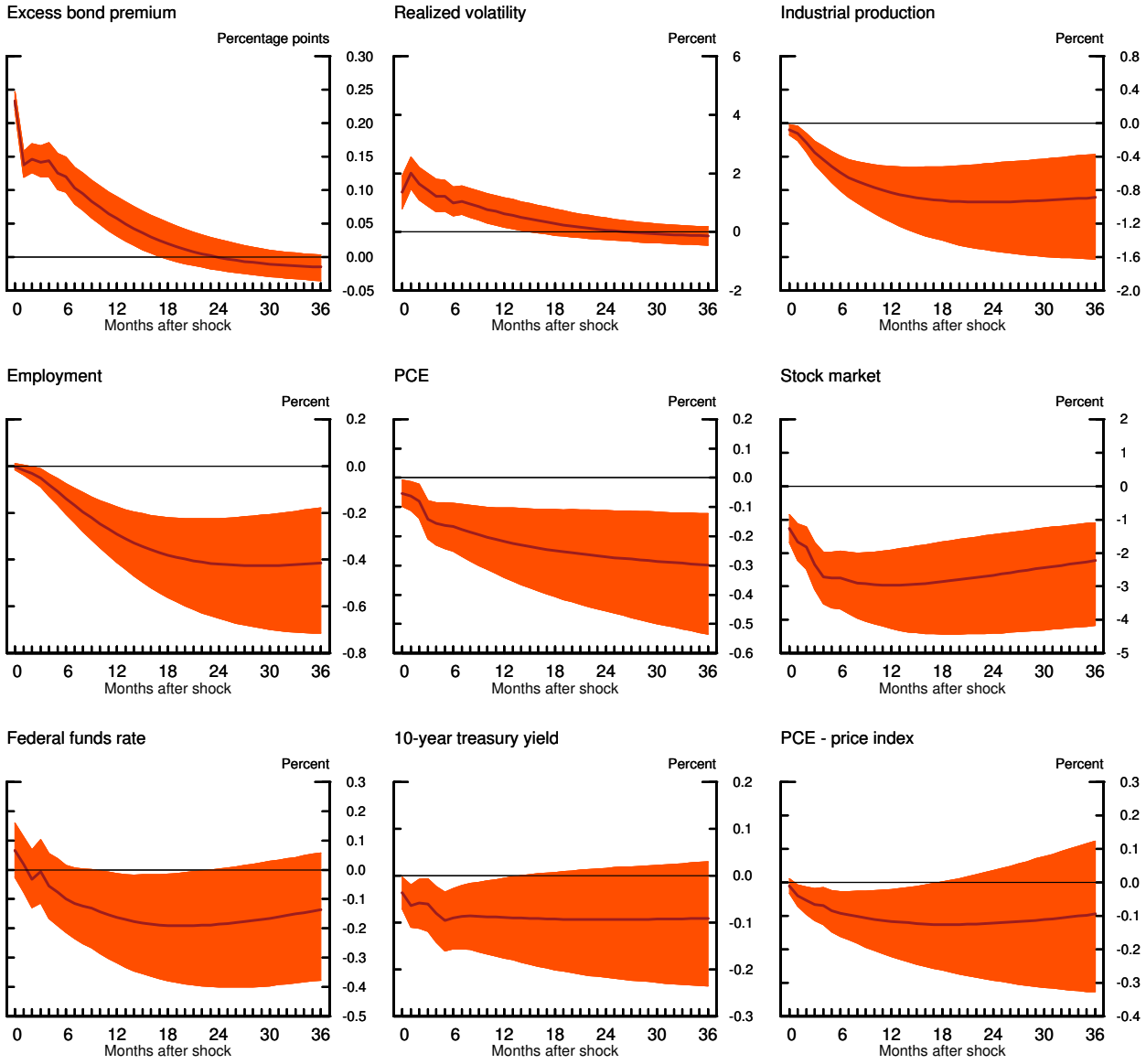
Table B.9: Multivariate Granger tests: conditioning on federal funds rate

$EBP_t = \alpha + \sum_{i=1}^{2} \beta_i EBP_{t-i} + \sum_{j=1}^{k} \gamma_j \sigma_{t-j} + \sum_{l=1}^{m} \phi_l ffr_{t-l} + \epsilon_t$						
σ	RVOL	IVOL	DISP	BBD	VXO	SRU
k	1	1	1	1	2	1
m	1	1	1	1	1	1
$\sum_{j=1}^{k} \gamma_k$	0.1036	0.0615	0.0162	0.0207	-0.1785	0.0240
95% CI	[0.0601, 0.1471]	[0.0060, 0.1169]	[-0.0144, 0.0467]	[-0.0416, 0.0829]	[-0.3077, -0.0493]	[-0.0321, 0.0801]
p-value for F-test	0.0000	0.0299	0.2986	0.5140	0.0001	0.4005
$\sigma_t = \alpha + \sum_{i=1}^{h} \beta_i \sigma_{t-i} + \sum_{j=1}^{k} \gamma_j EBP_{t-j} + \sum_{l=1}^{m} \phi_l EA_{t-l} + \epsilon_t$						
σ	RVOL	IVOL	DISP	BBD	VXO	SRU
h	2	2	2	4	1	1
k	1	1	1	1	1	1
m	1	1	1	1	1	1
$\sum_{j=1}^{k} \gamma_k$	0.2321	0.1006	-0.0125	0.0544	0.1515	0.2154
95% CI	[0.0654, 0.3987]	[0.0324, 0.1687]	[-0.0636, 0.0386]	[-0.0071, 0.1159]	[0.0564, 0.2466]	[0.0615, 0.3693]
p-value for F-test	0.0064	0.0039	0.6316	0.0828	0.0019	0.0059

Notes: The sample for all variables but SRU ranges from 1986:M1 to 2011:M12. The sample for SRU starts in 1991:M1.The linear regression models are estimated on standardized data using HAC-robust variance estimates. A test that σ_t does not Granger-cause EBP_t is an F-test of $H_0 : \gamma_j = 0, \forall j$.

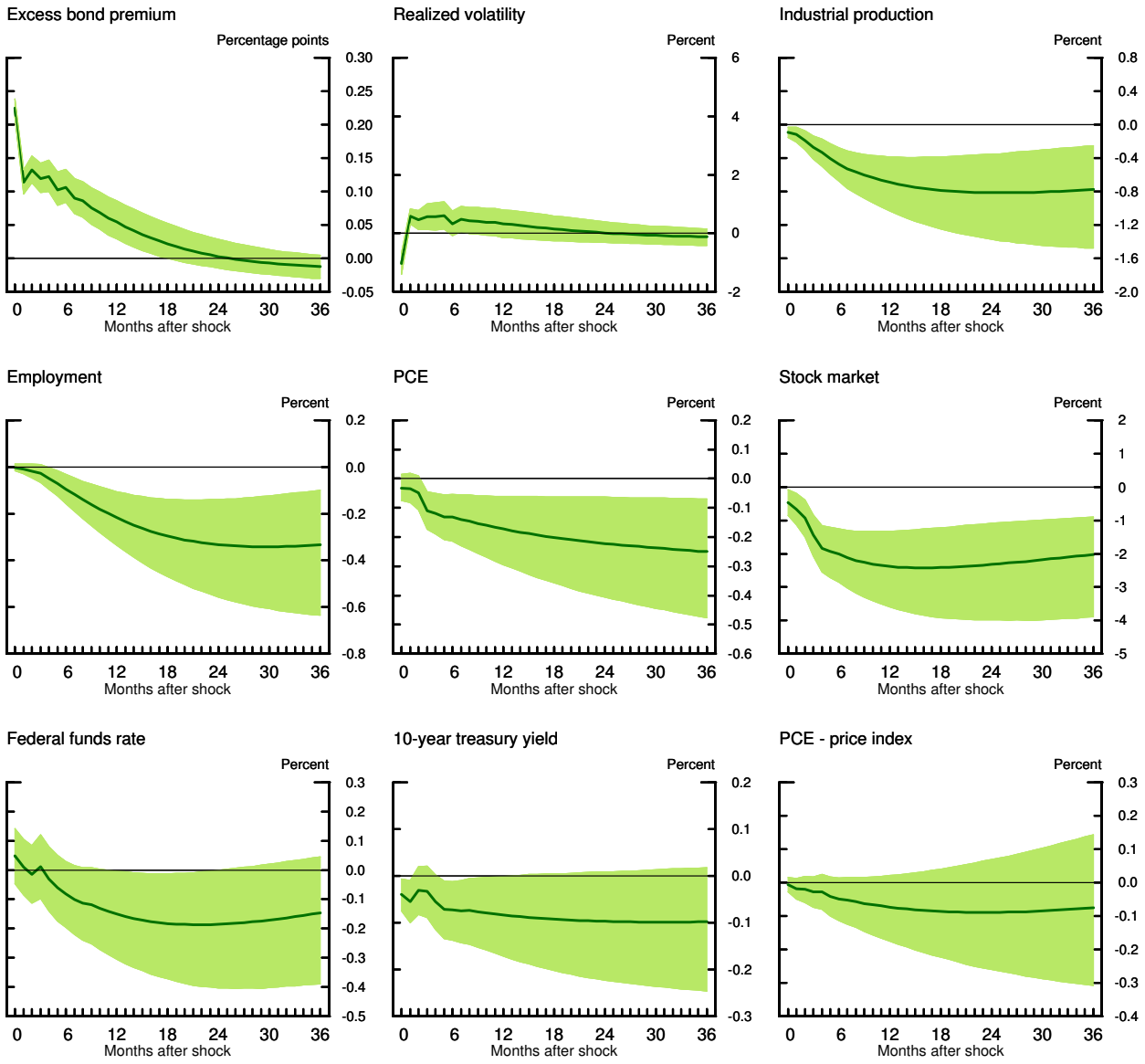
Appendix C. Figures

Figure C.1: Responses to a Financial Shock. Baseline identification.



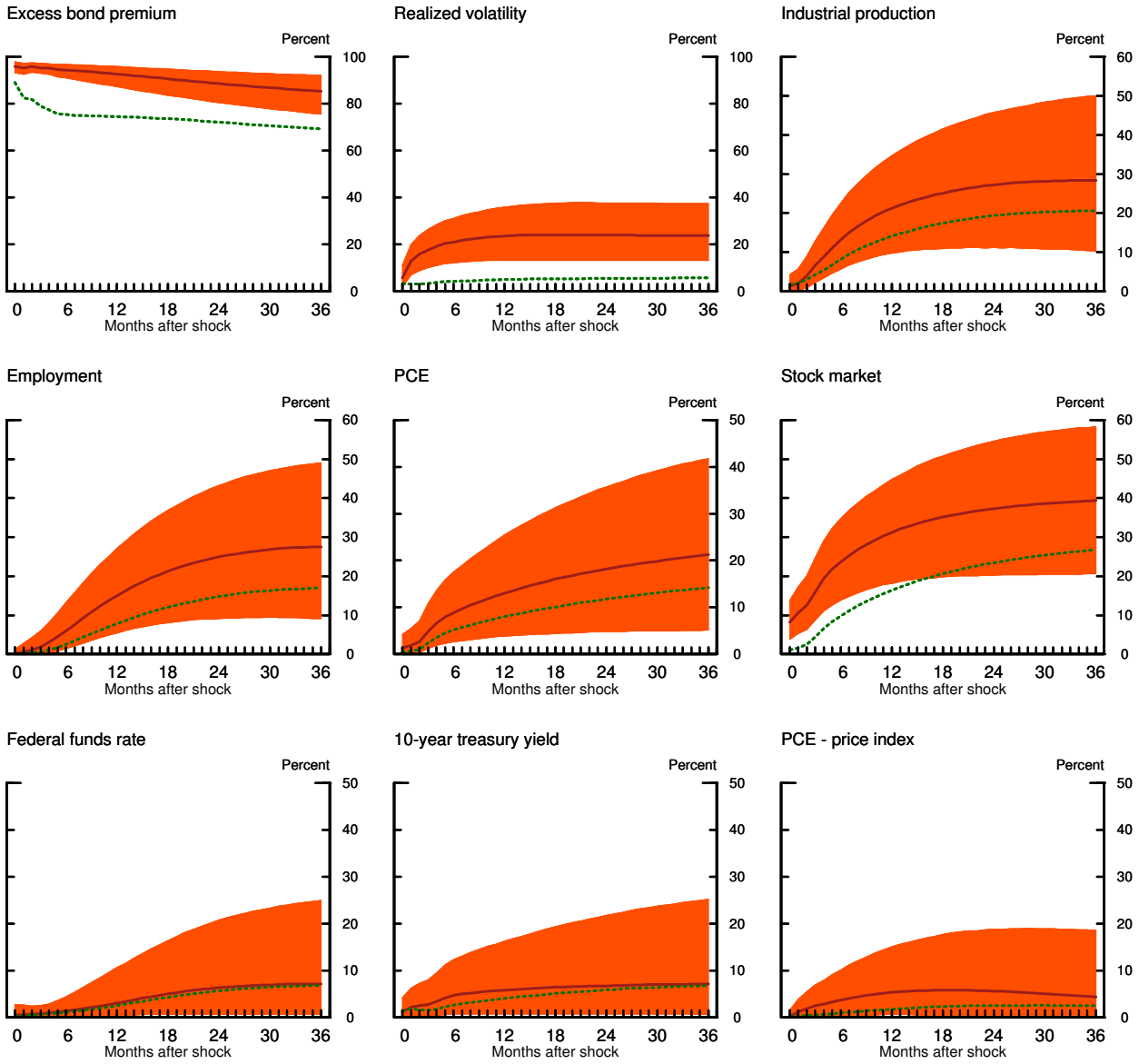
Notes: The solid line represents the median impulse response function. The bands correspond to the 95% confidence bands.

Figure C.2: Responses to a Financial Shock. Alternative identification.



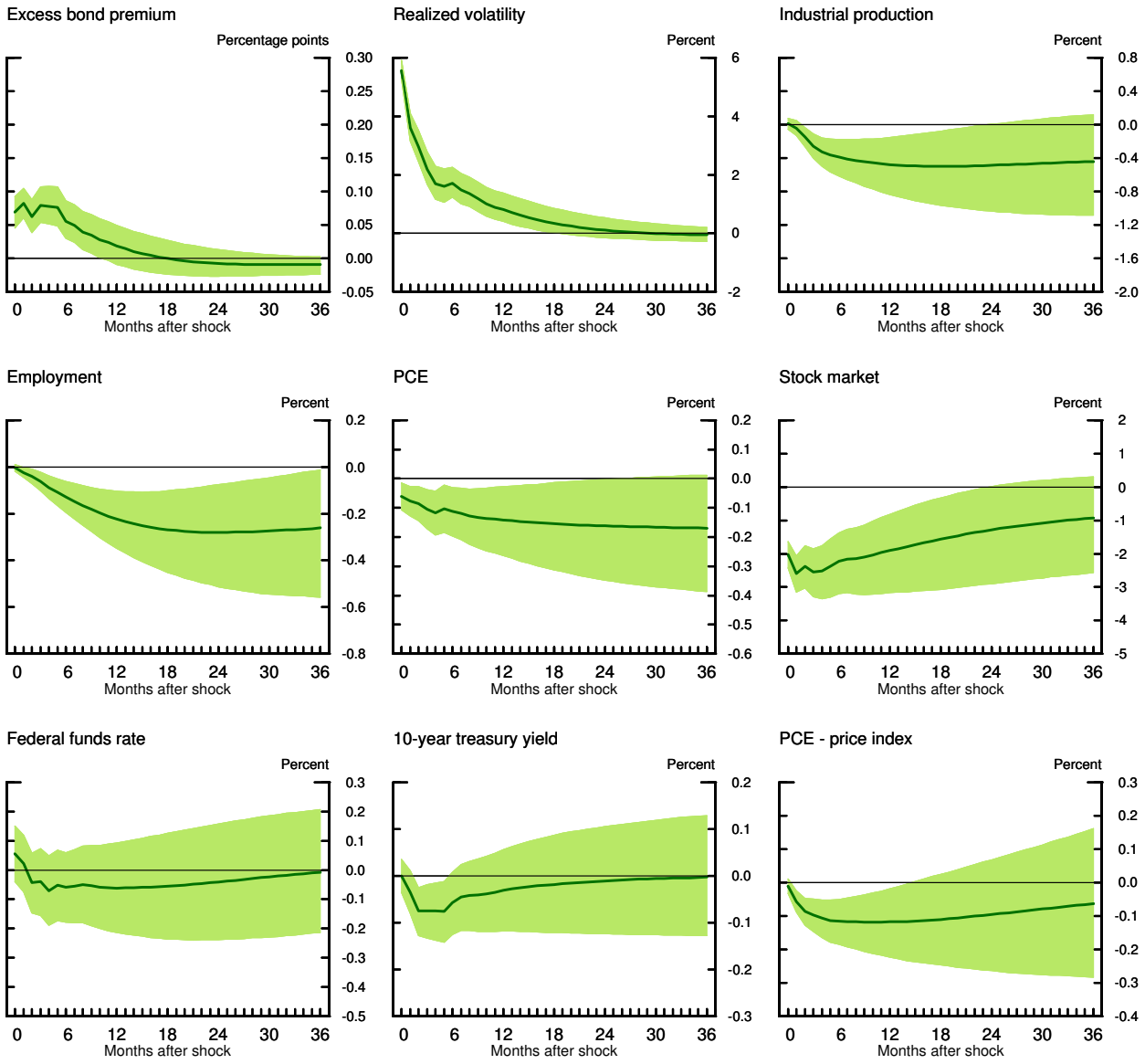
Notes: The solid line represents the median impulse response function. The bands correspond to the 95% confidence bands.

Figure C.3: FEVD to a Financial Shock



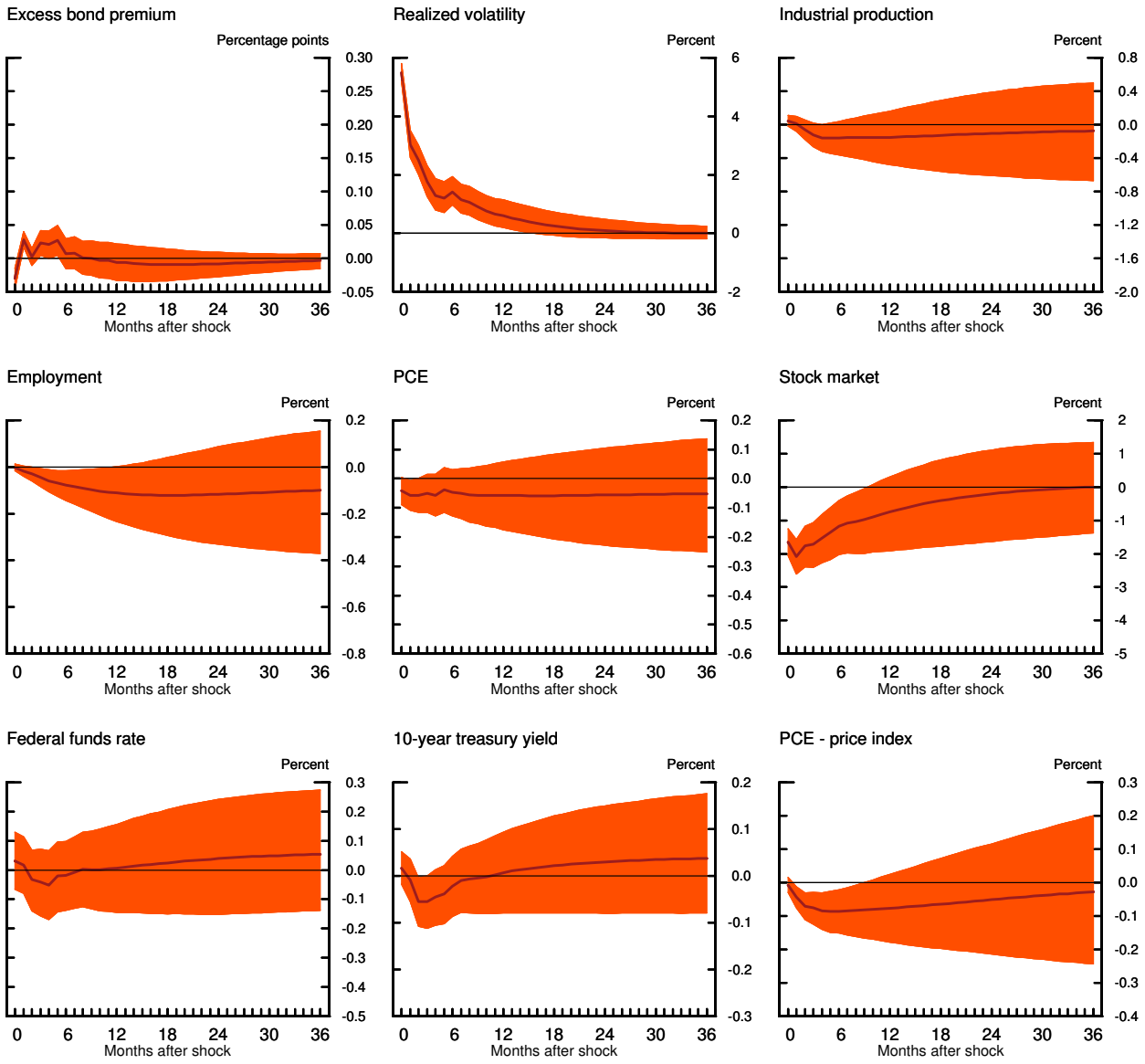
Notes: The solid red line and the band correspond to the median contribution of financial shocks to the FEV and the 95% confidence bands in the baseline identification. The green dotted line represents the median contribution of financial shocks under the alternative identification.

Figure C.4: Responses to an Uncertainty Shock. Alternative identification.



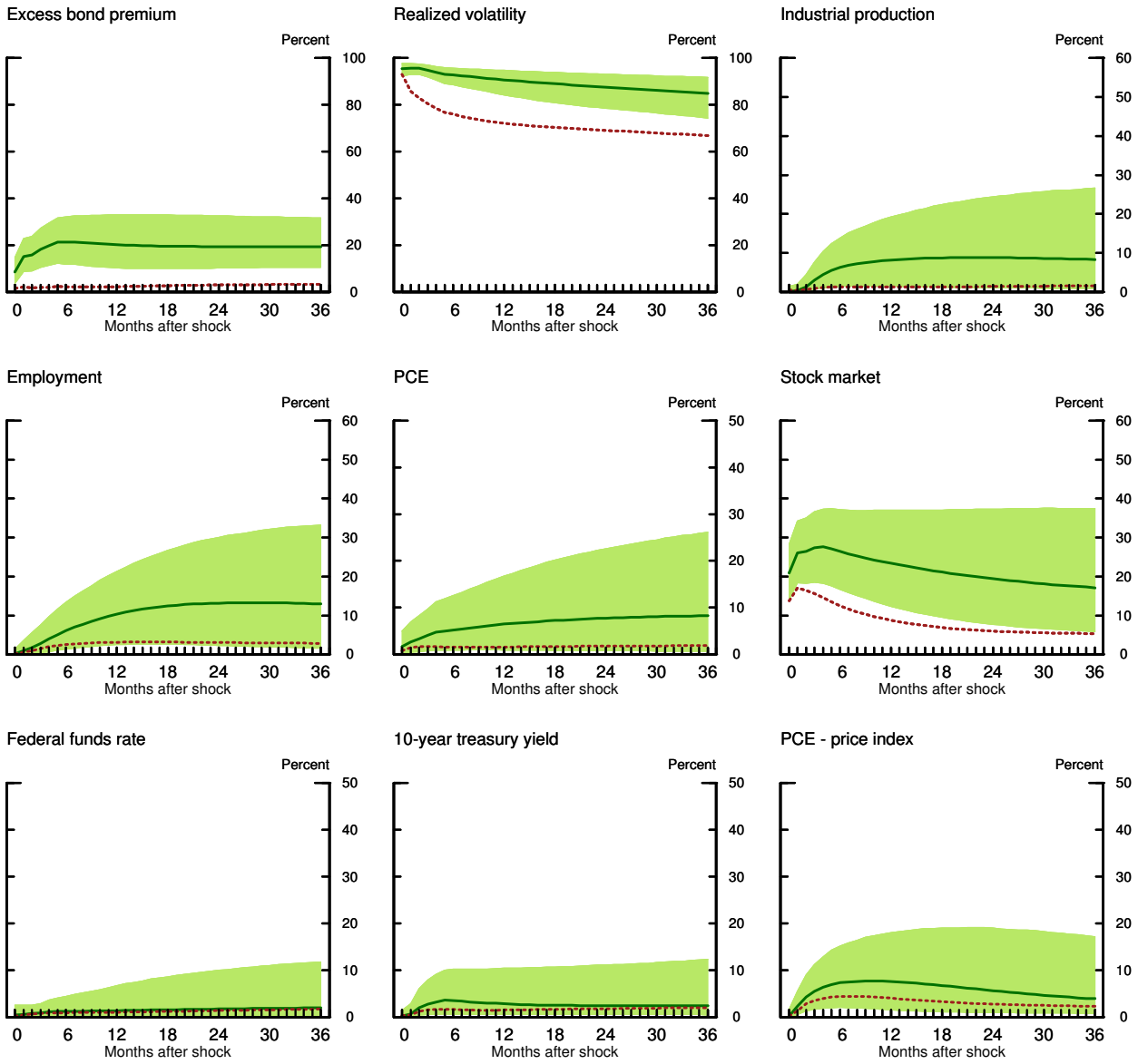
Notes: The solid line represents the median impulse response function. The bands correspond to the 95% confidence bands.

Figure C.5: Responses to an Uncertainty Shock. Baseline identification.



Notes: The solid line represents the median impulse response function. The bands correspond to the 95% confidence bands.

Figure C.6: FEVD to an Uncertainty Shock



Notes: The solid green line and the band correspond to the median contribution of uncertainty shocks to the FEV and the 95% confidence bands in the baseline identification. The red dotted line represents the median contribution of uncertainty shocks under the alternative identification.

Figure C.7: Historical Variance Decomposition: Alternative Identification Scheme

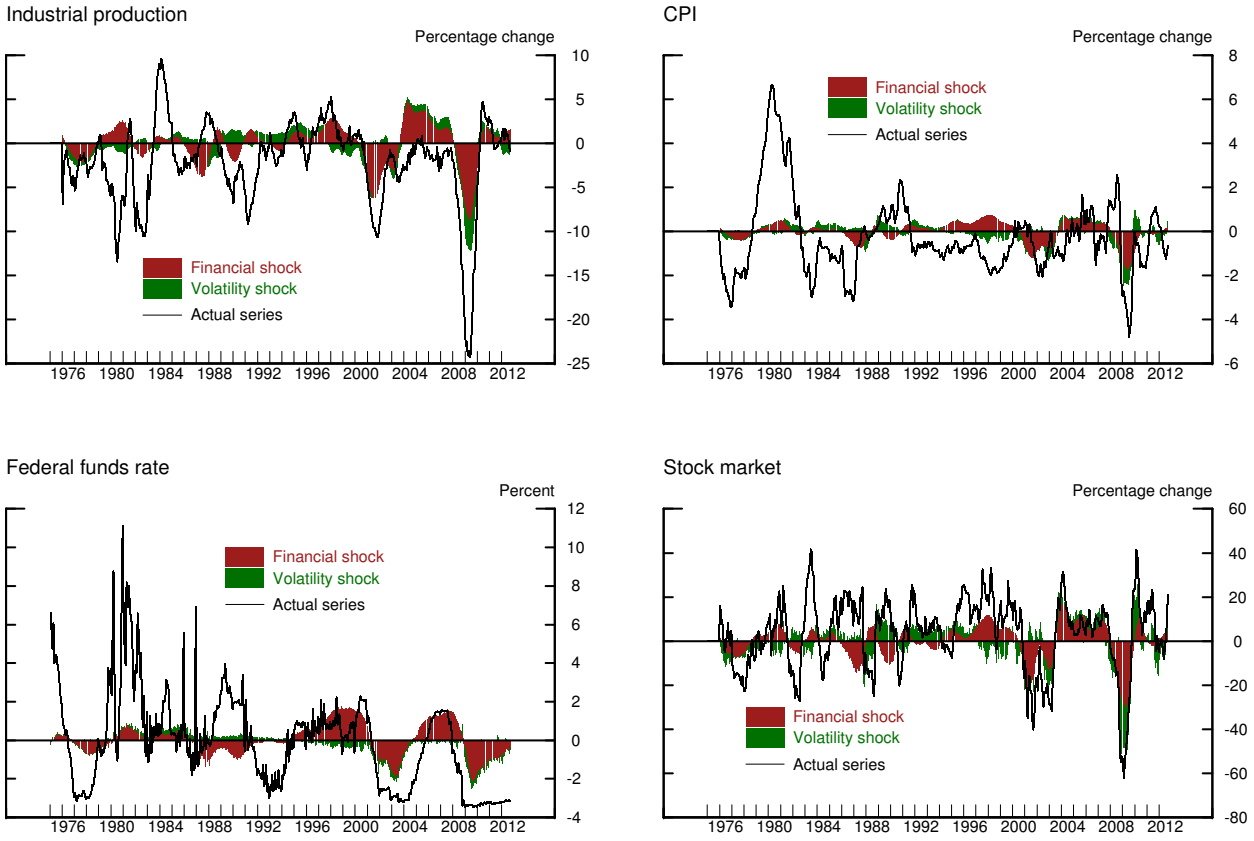
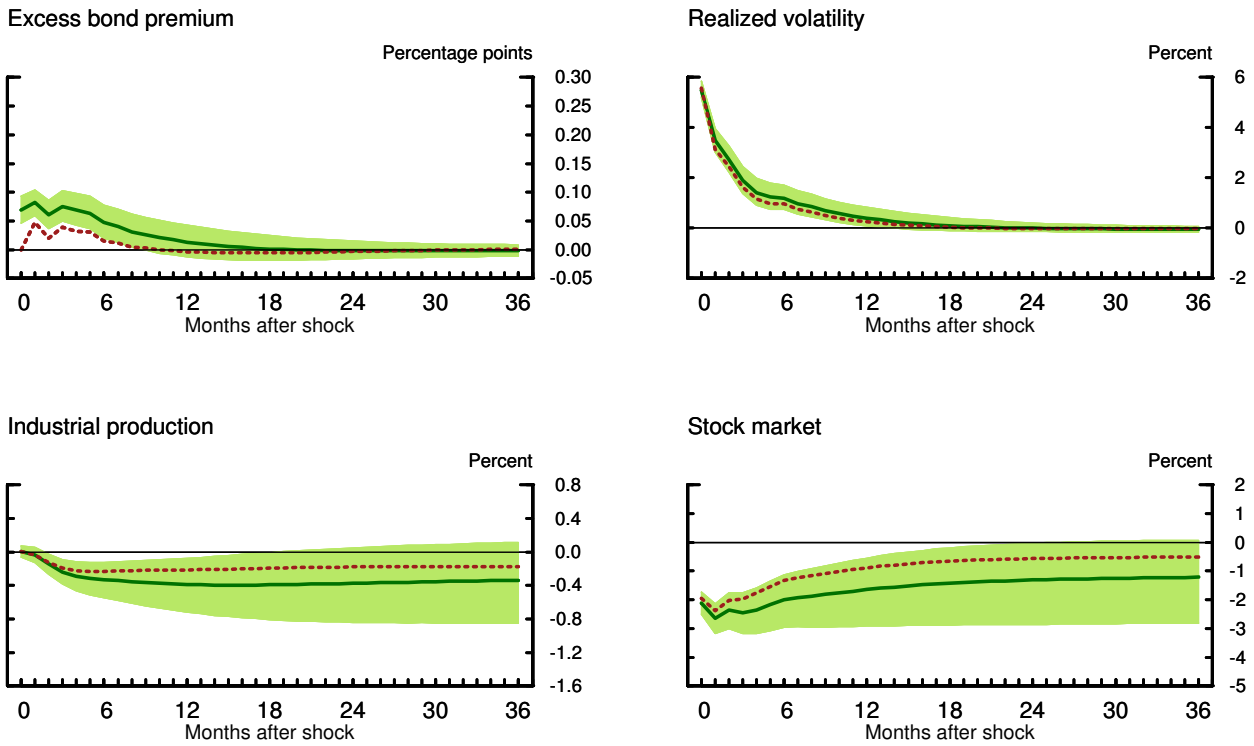
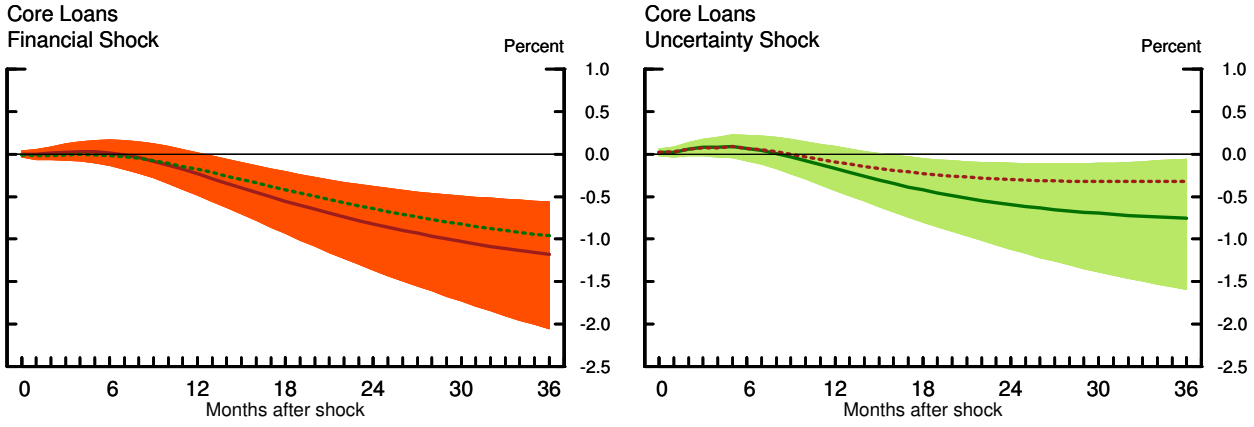


Figure C.8: Uncertainty Shock – Constrained Optimization Based Identification



Notes: The solid line and bands correspond to the median response and its 95% confidence interval to an uncertainty shock under the alternative identification. The dotted line represents the median response under the constrained alternative identification.

Figure C.9: Response of Bank lending (1985 - 2012)



Notes: The solid line corresponds to the median response to the corresponding shock when identified first. The color band corresponds to the 95% confidence interval for this case. The dotted line represents the median response to the shock when identified second.

Figure C.10: Response of Durables and Non-Durables

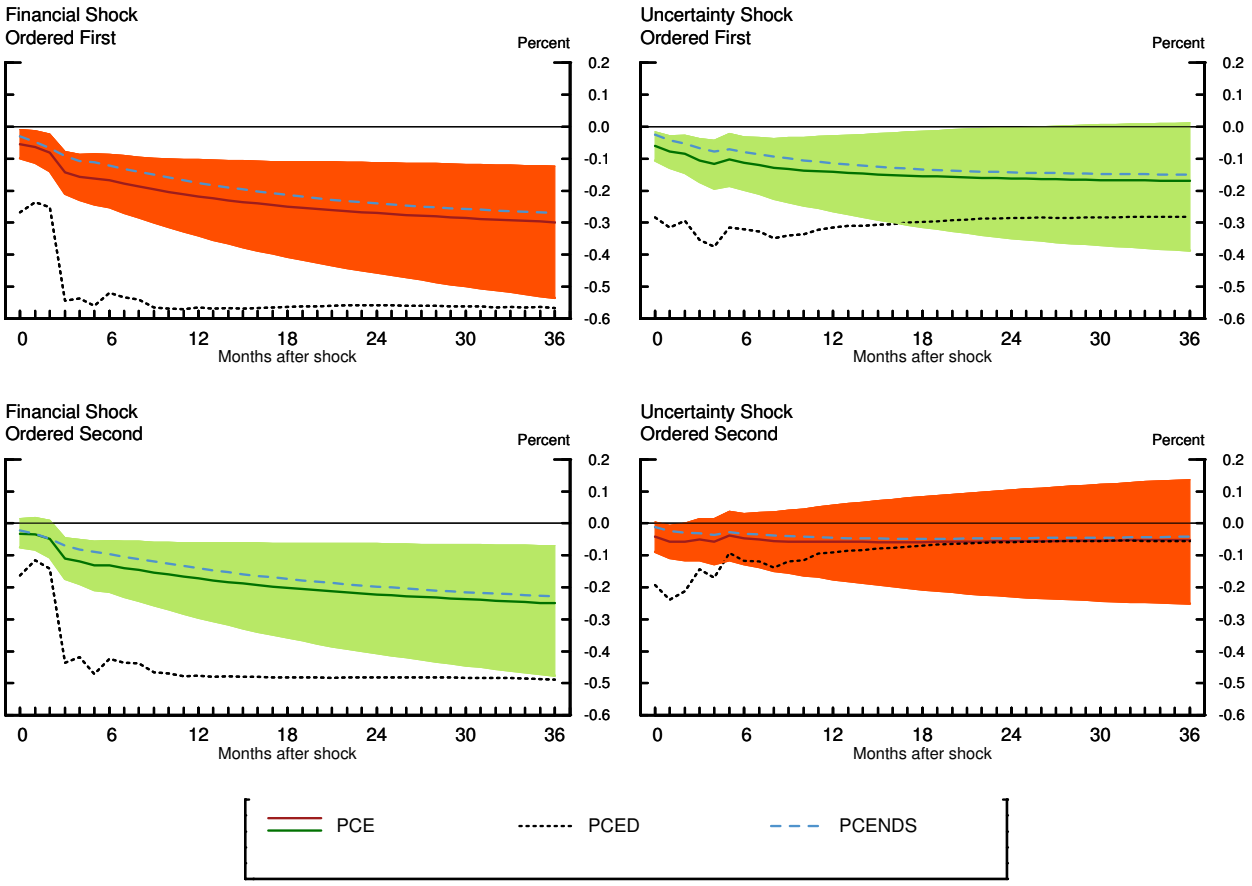


Figure C.11: Response of Net Worth and Leverage

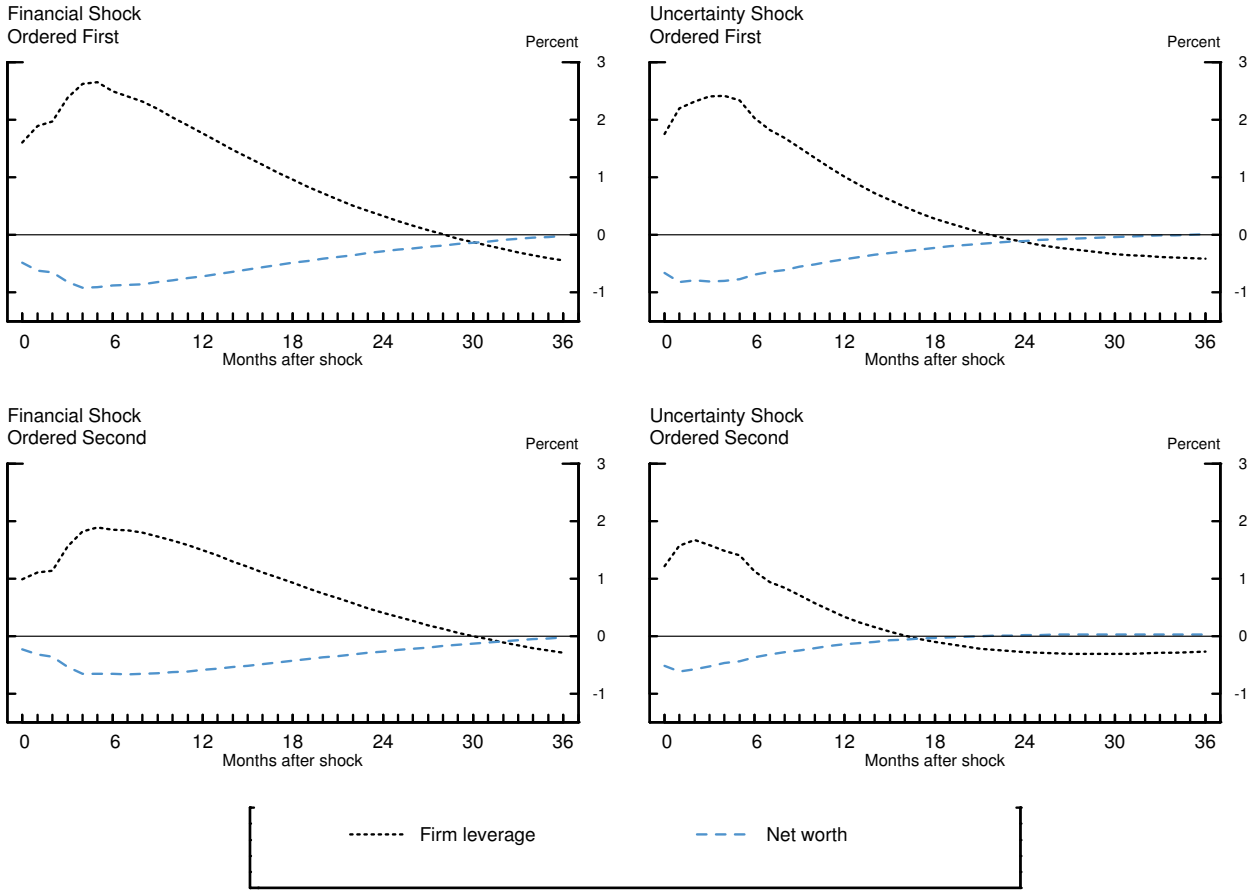


Figure C.12: Alternative Uncertainty Proxies: Financial Shock, Baseline Identification

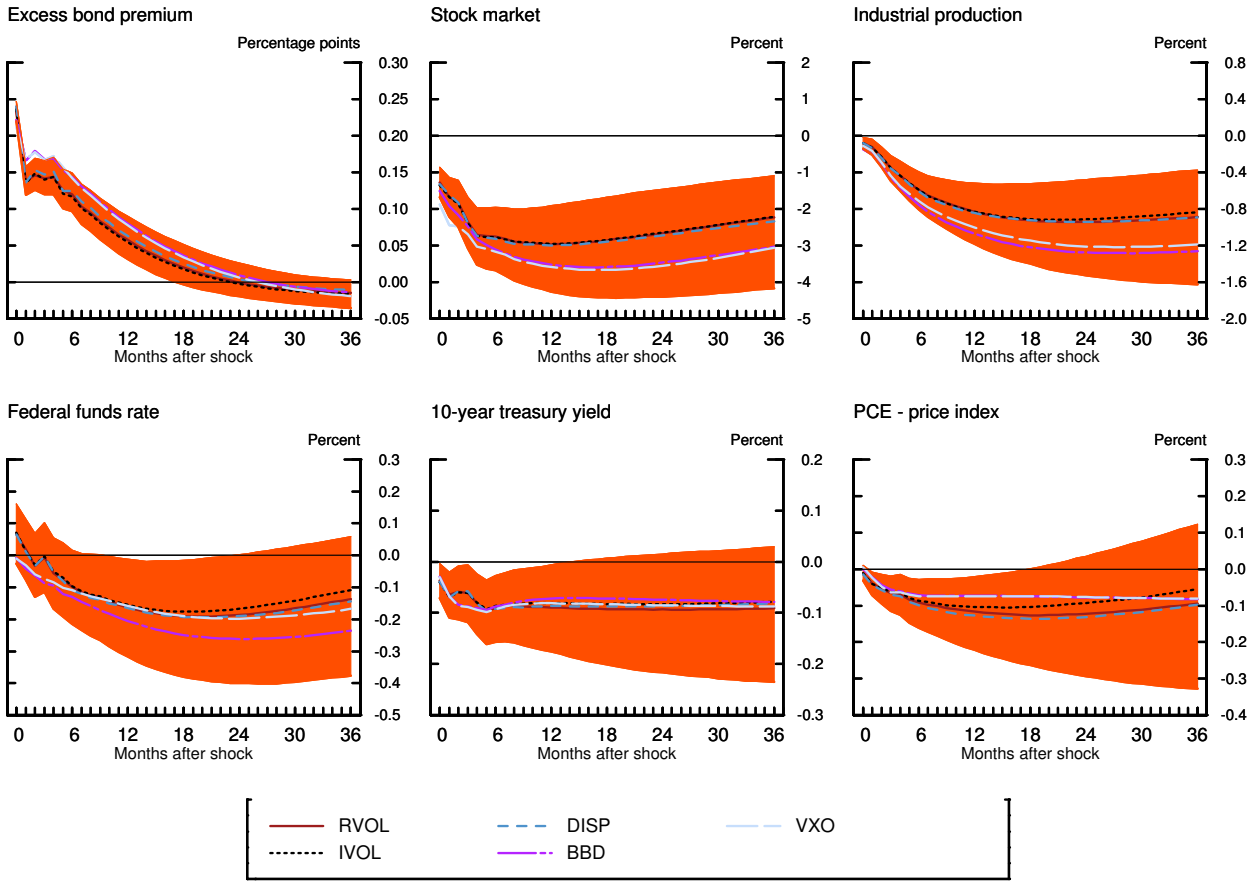


Figure C.13: Alternative Uncertainty Proxies: Financial Shock, Alternative Identification

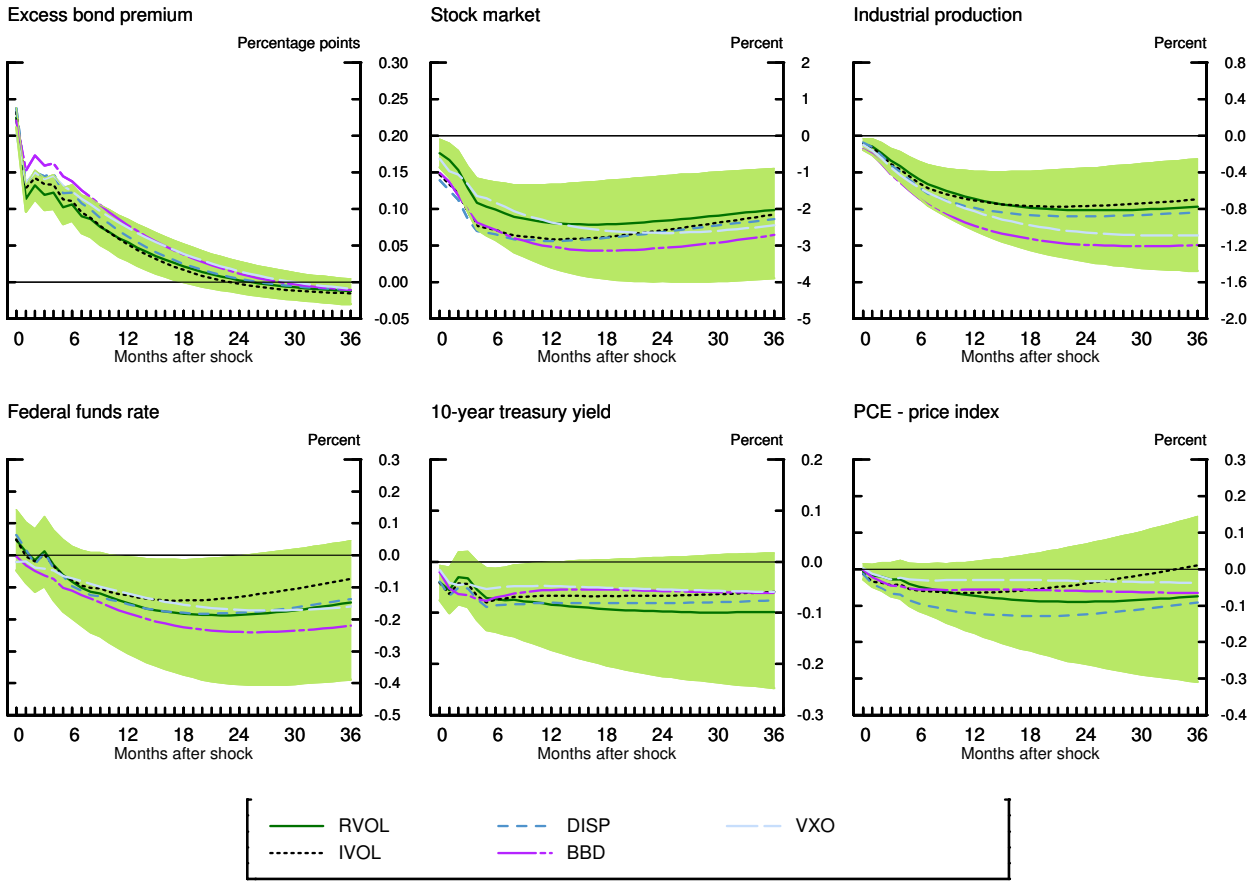


Figure C.14: Alternative Uncertainty Proxies: Uncertainty Shock, Alternative Identification

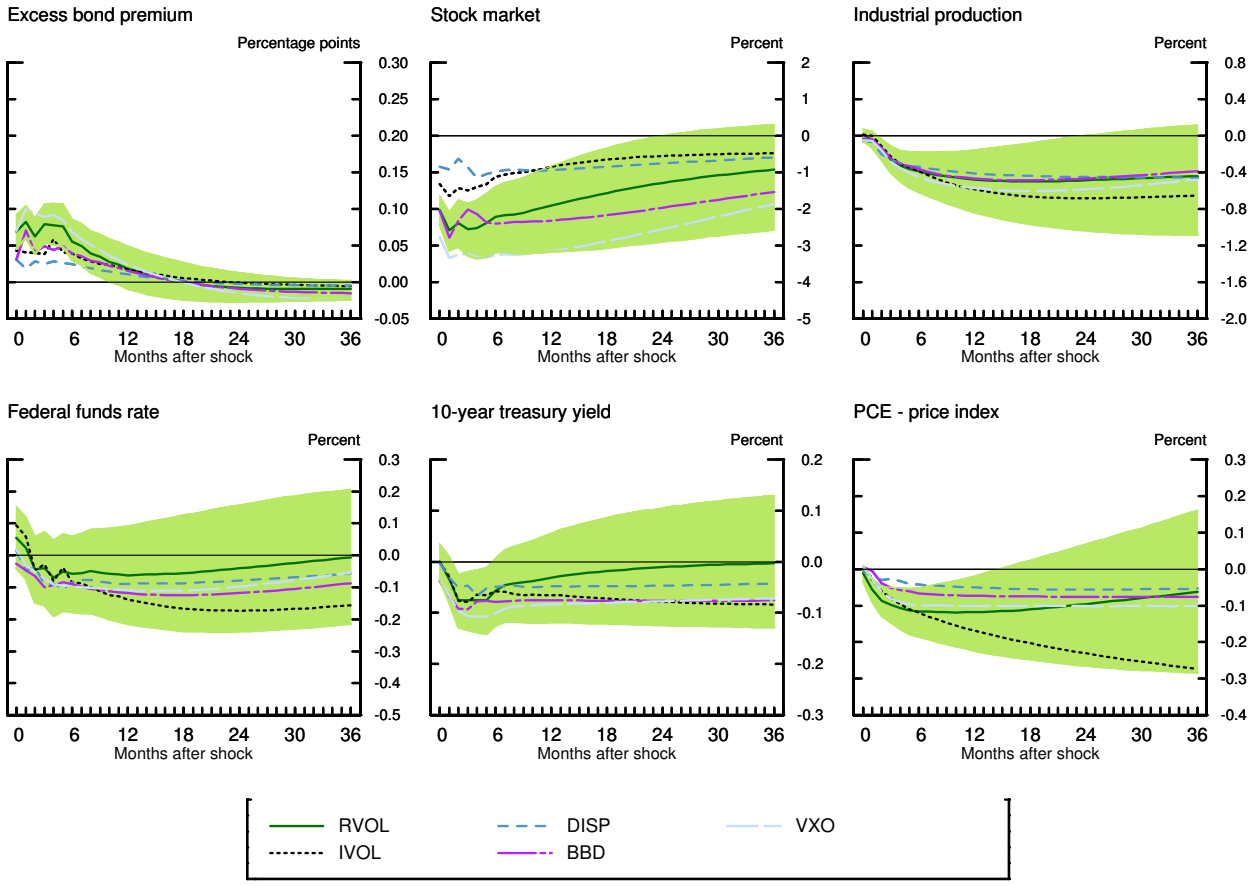


Figure C.15: Alternative Uncertainty Proxies: Uncertainty Shock, Baseline Identification

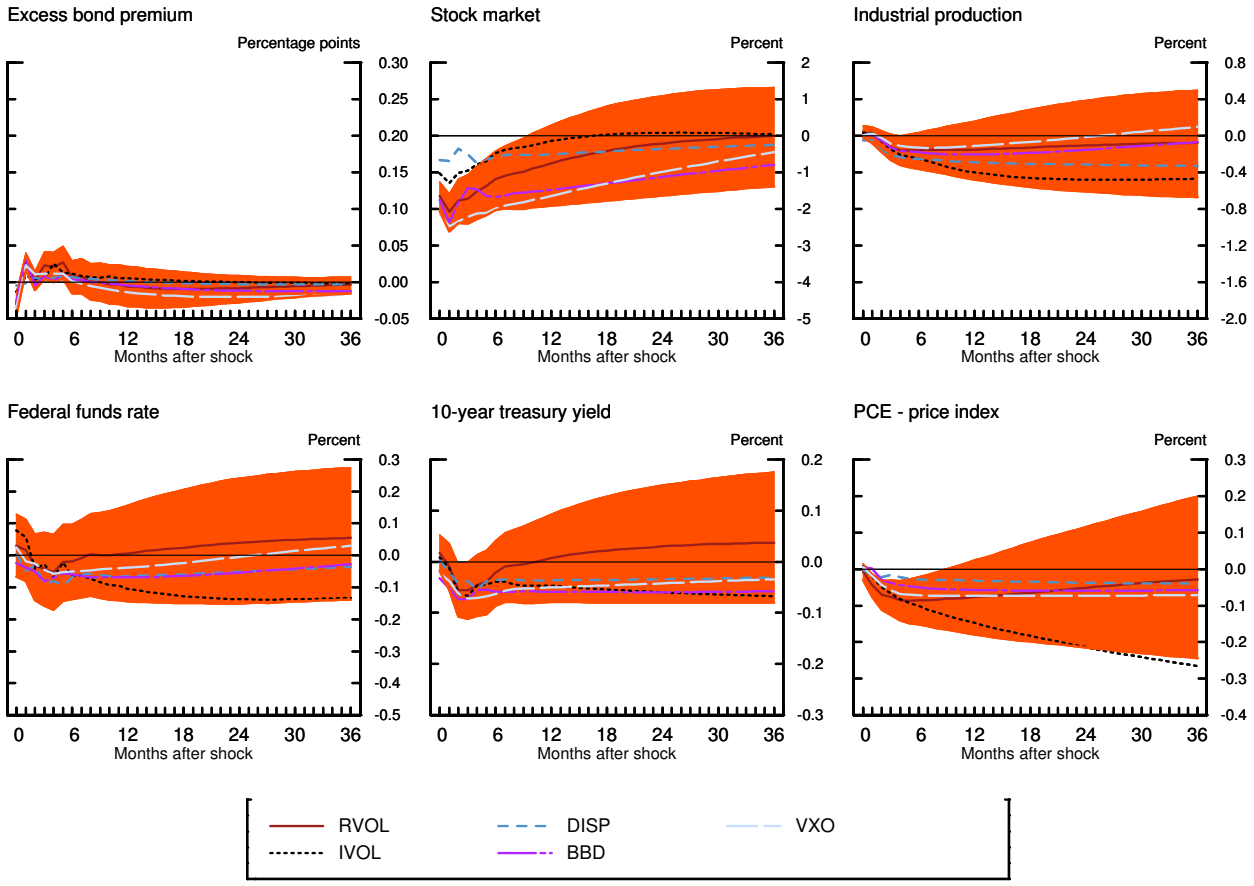


Figure C.16: Industrial Production: Model Specification, Sample, Identification

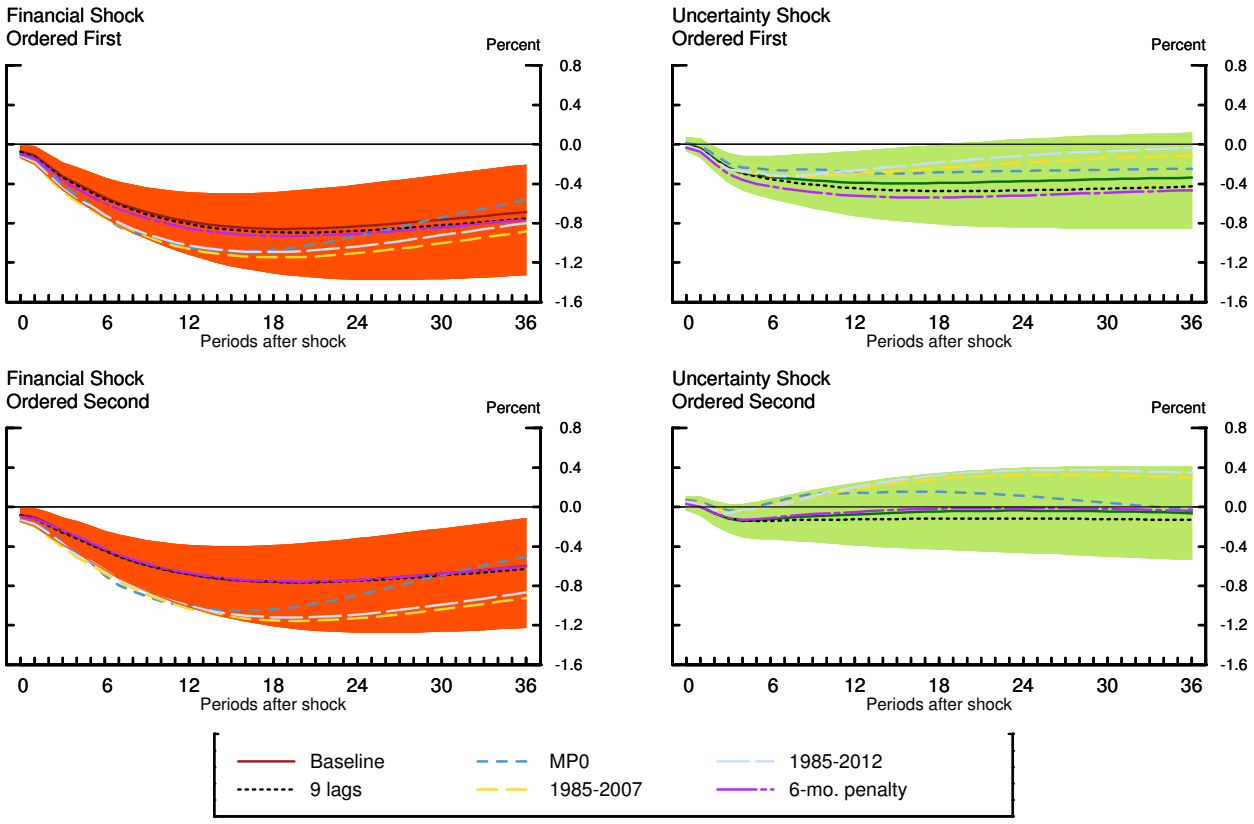


Figure C.17: Stock Market Returns: Model Specification, Sample, Identification

