The Macroeconomic Impact of Financial and Uncertainty Shocks

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September 9, 2014

Abstract

The extraordinary events surrounding the "Great Recession" have cast a considerable doubt on the traditional sources of macroeconomic disturbances. In their place, economists have singled out financial and uncertainty shocks as important drivers of economic fluctuations. Distinguishing between these two types of shocks, however, is difficult because increases in uncertainty are frequently associated with a widening of credit spreads, an indication of a tightening in financial conditions. This paper uses the penalty function approach to jointly identify shocks behind changes in financial conditions and economic uncertainty and to trace out the impact of these two types of shocks on the economy. Importantly, the identifying assumptions do not rule out a contemporaneous response of financial conditions to uncertainty shocks or vice versa. The results indicate that (1) financial shocks have a significant adverse effect on economic outcomes and that such shocks were an important source of cyclical fluctuations since the mid-1980; (2) uncertainty shocks have a significant macroeconomic impact in situations where they elicit a tightening of financial conditions; and (3) the rise in uncertainty in response to a financial shock suggests that swings in uncertainty are influenced importantly by changes in financial conditions.

JEL Classification: E32, E37, E44
Keywords: time-varying volatility; credit spreads; structural vector autoregression, optimization-based identification

We thank seminar and conference participants at the Federal Reserve Board; Georgetown University; the Federal Reserve Bank of Philadelphia; Bank of Portugal; Bank of Spain; the Swiss National Bank; the Inter-American Development Bank; the Guanghua School of Management, Tsinghua University; the 2013 SED Annual Meetings; the 2013 Workshop on Macroeconomics, Financial Frictions, and Asset Prices at the University of Pavia; the 9th Dynare Conference; the Summer 2013 Meeting of the North American Econometric Society; the Spring 2014 Midwest Macro Meeting; the 20th Conference in Computing in Economics & Finance; and the 37th Symposium of the Spanish Economic Association. Shaily Patel and Rebecca Zhang provided outstanding research assistance. All errors and omissions are our own responsibility. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of anyone else associated with the Federal Reserve System.

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1 Introduction

The acute turmoil that swept through global financial markets during the 2008–09 financial crisis and the depth and duration of the associated economic downturn, both in the United States and abroad, have cast considerable doubt on the traditional sources of business cycle fluctuations. In response, a flurry of theoretical and empirical research aimed at understanding these extraordinary events has pointed to financial or uncertainty shocks—or their toxic combination—as alternative drivers of economic fluctuations (see Bloom, 2009; Bloom et al., 2012; Arellano et al., 2012; Christiano et al., 2014; Gilchrist et al., 2014b). Empirically distinguishing between these two types of shocks, however, is difficult because increases in financial market volatility—a widely used proxy for economic uncertainty—are frequently associated with significant increases in credit spreads, a timely indicator of disruptions in financial markets.[1]

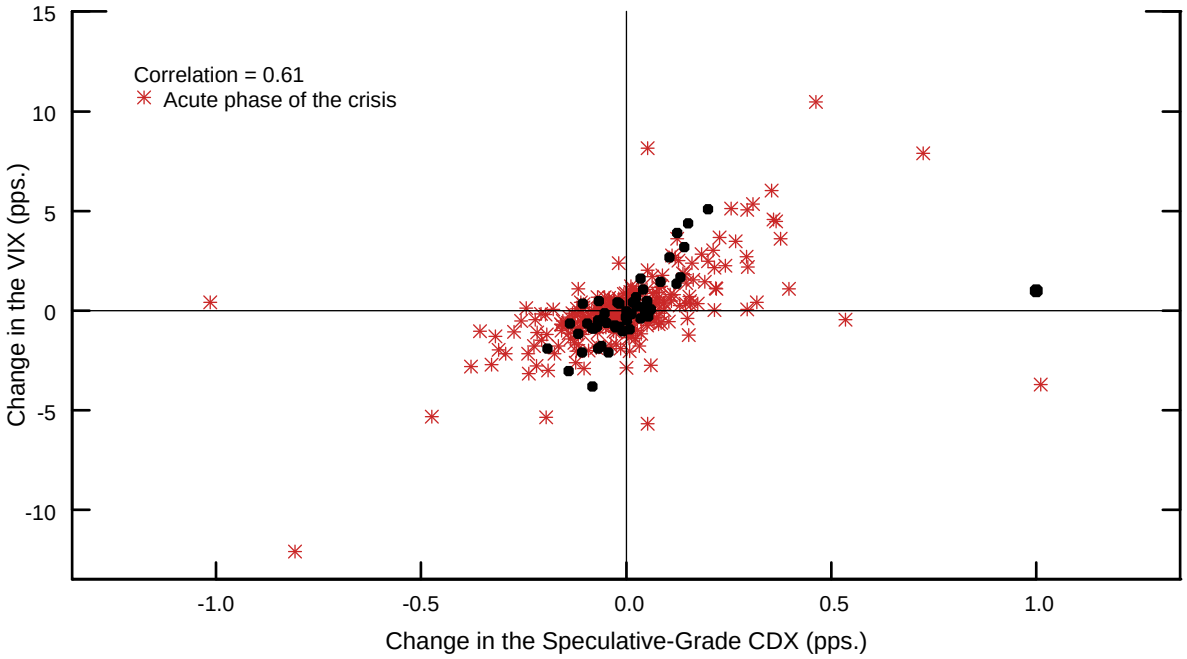
A stark illustration of this empirical challenge is depicted in Figure 1, which shows the relationship between the daily change in the option-implied volatility on the S&P 500 stock futures index (the VIX) and the daily change in the speculative-grade CDX index during the "Great Recession."[2] Clearly evident is the fact that episodes of acute financial distress are associated with significant spikes in asset price volatility. Indeed, in their comprehensive empirical anatomy of the Great Recession, Stock and Watson (2012) explicitly single out the high (positive) correlation between credit spreads and proxies for economic uncertainty and conclude that "[T]hese two sets of instruments do not seem to be identifying distinct shocks."

The identification of financial and uncertainty shocks within a structural vector autoregressive (SVAR) framework—the workhorse of empirical macroeconomics—is complicated by the fact that indicators of financial distress such as credit spreads and volatility-based uncertainty proxies are both "fast-moving" variables. As a result, it is difficult to impose plausible zero contemporaneous restrictions to identify these two types of disturbances. 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 theoretically the same qualitative effects on both prices and quantities in most instances.

[1] The fact that the level of credit spreads is highly informative about the tightness of financial conditions in the economy and thus the implied degree of departure from the Modigliani–Miller paradigm of frictionless financial markets is supported by the rapidly growing empirical literature showing that corporate bond credit spreads form the most informative and reliable class of financial indicators for future economic activity and that unanticipated increases in credit spreads have large and persistent adverse effects on the macroeconomy (see Gertler and Lown, 1999; Mueller, 2009; Gilchrist et al., 2009; Gilchrist and Zakrajšek, 2012; Bleaney et al., 2012; Boivin et al., 2013; Faust et al., 2013; Gilchrist and Mojon, 2014).

[2] The VIX index is a commonly used proxy for economic uncertainty (see Bloom, 2009). The speculative-grade CDX index is a tradable credit derivative index used widely by investors for hedging of and investing in corporate credit risk. Buying and selling of the credit derivative index is comparable to buying and selling portfolios of corporate cash instruments: By buying the index, the investor takes on the credit exposure—is exposed to defaults—a position similar to that of buying a portfolio of bonds; by selling the index, the credit exposure is passed on to another party. The speculative-grade CDX index references 100 (5-year) credit default swap (CDS) contracts on firms that have a "junk" rating from either Moody's or Standard & Poor's. The component firms must have highly liquid single-name CDS trading in their name, and the composition of both indexes, which is determined by a dealer poll, is representative of the U.S. corporate sector.

Figure 1: Financial Market Volatility and Credit Risk During the Great Recession



NOTE: Sample period: daily data from 12/01/2007 to 06/30/2009. The scatter plot depicts the relationship between the daily change in the option-implied volatility on the S&P 500 stock futures index (VIX) and the daily change in the 5-year (on-the-run) speculative-grade CDX index. The period 09/01/2008 to 08/05/2009 marks the acute phase of the crisis, which reached a critical stage in early September 2008, when an evaporation of liquidity in the global credit markets threatened the solvency of several major financial institutions. The end date of the acute phase follows the release of the results from the Supervisory Capital Assessment Program (the so-called bank stress test) at 5 p.m. EST on May 7, 2009.

In this paper, we use the penalty function approach developed initially by Faust (1998) and Uhlig (2005) to identify shocks behind changes in financial conditions and economic uncertainty and to trace out the impact of these two types of disturbances on the macroeconomy. Within our VAR framework, the two structural innovations are identified using a criterion that each shock should maximize the *impulse response* of its respective target variable over a pre-specified horizon. This quantitative criterion allows us to distinguish between shocks that have otherwise very similar qualitative effects on the macroeconomy.

Because this approach requires a sequential identification of shocks, we implement the penalty function criterion in two steps. In the baseline identification, we first search for an innovation that maximizes the response of the financial stress variable over a given horizon—this optimization step identifies what we call a "financial shock." In the second step, we search for an innovation that maximizes the response of the uncertainty proxy over the same horizon and that is orthogonal to the financial shock identified in the first step—we call this shock an "uncertainty shock."

We also consider an alternative identification scheme that reverts the ordering of the two penalty function steps to identify these two types of disturbances. Both of our identification strategy effec-

tively assume that the unanticipated changes in financial conditions are due primarily to financial shocks, whereas fluctuations in economic uncertainty are driven mainly by uncertainty shocks. Importantly, neither identification schemes rules out a contemporaneous response of financial conditions to uncertainty shocks or vice versa. It is also worth emphasizing that our approach differs from the pure sign restriction identification schemes in that it identifies a single structural VAR specification, rather than a set of models (see Fry and Pagan, 2011; Caldara and Kamps, 2012; Arias et al., 2013).

In implementing this approach, we consider a standard monetary VAR, augmented with an indicator of financial conditions and a proxy for macroeconomic uncertainty. To measure strains in financial markets, we use the excess bond premium (EBP), an indicator of the effective "risk-bearing capacity" of the financial intermediary sector, developed recently by Gilchrist and Zakrajšek (2012). In the benchmark VAR specification, we use the realized stock market volatility as a proxy for economic uncertainty because of its intuitive appeal and because this measure is available over the longest time period. However, we also perform an extensive sensitivity analysis by considering other commonly used indicators of macroeconomic uncertainty, including the option-implied volatility of equity returns (Bloom, 2009); the common component of the idiosyncratic equity volatility (Gilchrist et al., 2014b); the cross-sectional dispersion of survey-based forecasts of economic outcome indicators (Bachmann et al., 2013); an economic policy uncertainty index (Baker et al., 2013); and an index of how uncertain agents are about current economic conditions based on economic data releases (Scotti, 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. In addition, the stock market falls substantially, and share prices remain depressed for a considerable period of time. These dynamics are consistent with our maintained assumption that shocks to the EBP are capturing disruptions in the credit-intermediation process and their attendant economic consequences. In the baseline identification scheme, financial shocks account for about one-third of the variation in industrial output, payroll employment, and broad equity valuations at business cycle frequencies, proportions indicating that such shocks are an important source of business cycle fluctuations.

Macroeconomic implications of financial disruptions identified vis-à-vis shocks to the EBP using the alternative identification scheme are very similar: An adverse financial shock induces a broad-based deterioration in economic activity and labor market conditions and leads to a sharp and permanent drop in stock prices. Interestingly, this shock has no effect of the level of uncertainty in the economy under the alternative identification scheme. It is also worth noting that this absence of transmission of financial shocks through changes in economic uncertainty is a data-driven outcome of the analysis and does not reflect a zero restriction as in, for example, a Cholesky identification scheme.

The results also indicate that uncertainty shocks have a meaningful macroeconomic impact in situations where they elicit a significant and persistent response of the EBP—that is, a tighten-

ing of financial conditions—as in under the alternative identification, a result consistent with the recent work of Arellano et al. (2012), Christiano et al. (2014), and Gilchrist et al. (2014b). In the baseline identification scheme, by contrast, the impact of uncertainty shocks on economic activity is significantly attenuated and has no effect on financial conditions, even though the identification scheme allows the EBP to respond contemporaneously to an uncertainty innovation. The fact that uncertainty increases upon impact in response to a financial shock also raises the possibility that swings in uncertainty are influenced importantly by changes in financial conditions, suggesting that heightened economic uncertainty may be a symptom, rather than a cause, of financial instability. This empirical result is consistent with the theoretical work of Van Nieuwerburgh and Veldkamp (2006), Fostel and Geanakoplos (2012), and Bachmann and Moscarini (2012), who show that spikes in uncertainty may be the result of a deterioration in macroeconomic conditions rather than an independent source of cyclical fluctuations.

2 Related Literature

By and large, the empirical literature seeking to quantify the macroeconomic impact of financial and uncertainty shocks has treated these two types of disturbances separately. Within the context of VAR models, financial shocks are typically identified using either sign or zero restrictions. For example, Gilchrist and Zakrajšek (2012) assume that shocks to the EBP affect real economic activity and inflation with a lag, but they have a contemporaneous effect on the short- and long-term risk-free rates and stock prices. Using a time-varying parameter VAR model, Prieto et al. (2013) make a similar identifying assumption by allowing shocks to credit spreads to affect real and nominal variables with a lag, while financial variables can react contemporaneously to such a disturbance.

The identification of financial shocks in data-rich environments generally relies on similar timing restrictions. Using security-level data, Gilchrist et al. (2009) construct an array of credit spread portfolios sorted by the issuer's ex-ante expected likelihood of default and the bond's remaining term-to-maturity. By building bond portfolios from the "ground up," they can also construct portfolios of stock returns—sorted by the same default risk categories—corresponding to the firms that issued those bonds. These matched portfolios of stock returns serve as controls for news about firms' future earnings as these borrowers experience shocks to their creditworthiness. Within a structural factor-augmented vector autoregression (FAVAR), Gilchrist et al. (2009) identify financial shocks from the corporate bond spreads that are orthogonal to general measures of economic activity, inflation, real interest rates, and various financial indicators, as well as to equity returns of firms whose outstanding bonds were used to construct credit spreads in the bond portfolios.

In contrast, Boivin et al. (2013) rely on a single credit spread index to identify financial shocks within several large-scale FAVAR specifications. Their identifying assumptions restrict a small subset of endogenous variables from responding contemporaneously to innovations in the representative credit spread. Regardless of the approach used to identify financial shocks, the above

papers uniformly find that an unanticipated deterioration in credit conditions—identified vis-à-vis a widening of corporate bond credit spreads—leads to substantial and long-lasting declines in economic activity. Moreover, the decomposition of the forecast error variance implies that these financial disruptions account for a sizable fraction of the variation in economic activity at business cycle frequencies.

A related strand of this literature relies on sign restrictions to identify financial shocks. Although the technical details differ from paper to paper, the general idea underlying this approach is that adverse credit supply shocks should lead to a decrease in the quantity of credit, while simultaneously increasing credit spreads or lending rates (see Helbling et al., 2011; Eickmeier and Ng, 2011; Hristov et al., 2012; Gambetti and Musso, 2012; Meeks, 2012; Peersman and Wagner, 2014). Consistent with the literature that relies on timing restrictions to identify credit supply shocks, the overall conclusion from sign-based SVAR identification schemes is the same: The identified exogenous financial shocks are a substantial source of macroeconomic fluctuations, with adverse credit supply shocks inducing a persistent decline in both output and inflation. However, as shown theoretically by Arellano et al. (2012), Christiano et al. (2014), and Gilchrist et al. (2014b), the same sign restrictions will also characterize the response of these variables to an uncertainty shock when financial markets are subject to agency problems.

The empirical literature on uncertainty shocks, in contrast, relies almost exclusively on zero restrictions to trace out the effects of such shocks on the macroeconomy. In his seminal paper, Bloom (2009) identifies uncertainty shocks by placing the VIX index after the stock market return but before the real and nominal blocks of the monthly VAR system. Thus, the transmission of uncertainty shocks through the equity market is ruled out a priori upon impact, and uncertainty innovations have a negligible contemporaneous effect on economic activity. However, once the financial channel opens up—that is, a month after the shock—positive innovations in the VIX index generate a sharp drop in industrial output followed by some overshooting, a pattern consistent with the "wait-and-see" effect of positive uncertainty shocks.[3] Bloom et al. (2012) confirm the robustness of this result by considering alternative measures of uncertainty computed from plant-level data—namely, the cross-sectional dispersion of total factor productivity (TFP) and output growth.

In an influential recent paper, Baker et al. (2013) introduce a different notion of uncertainty—macroeconomic policy uncertainty. In their monthly VAR specification, the policy uncertainty index is ordered before the stock market return—as well as the real and nominal blocks of the system—thus allowing uncertainty shocks to have a contemporaneous effect on the stock market. According to their results, unanticipated increases in policy uncertainty induce a persistent and significant decline in economic activity, corroborating the earlier results that uncertainty shocks are an important source of cyclical fluctuations.[4]

[3]Similar results are obtained in the international context by Carrière-Swallow and Cespedes (2013).

[4]In a closely related work, Mumtaz and Surico (2013) consider different sources of macroeconomic policy uncertainty—uncertainty about government spending, taxes, public debt sustainability, and monetary policy—and find that uncertainty about debt sustainability is the most important aspect of policy uncertainty.

Bachmann et al. (2013), in contrast, construct a survey-based measure of uncertainty from the disagreement in business expectations regarding outcome variables such as sales, employment, and hours worked.[5] Compared with the results of Bloom (2009), their findings indicate that the unanticipated increases in business uncertainty have negligible near-term economic effects, though adverse uncertainty shocks do lead to a persistent and prolonged decline in economic activity. However, once they include a survey-based measure of business confidence in their VAR specifications, the long-run impact of uncertainty innovations ceases to be economically important, and they argue that increases in uncertainty are a reflection of economic downturns rather than an independent driver of cyclical fluctuations.[6]

The evidence from survey-based measures of uncertainty is far more equivocal, however. Leduc and Liu (2014) exploit the fact that some consumer and business surveys tally responses that make explicit references to "uncertainty," insofar it affects the decisions of consumers to purchase big ticket items or firms' decision to expand their capital outlays. Using such direct measures of perceived uncertainty in a small-scale VAR, which, other than a short-term nominal risk-free rate, does not include any other financial variable, they find that the effects of uncertainty shocks on unemployment and inflation are similar to those of standard aggregate demand shocks. Jurado et al. (2013) propose yet another measure of economic uncertainty: A common factor extracted from a panel containing the unforecastable component of a large number of monthly economic and financial indicators. Interestingly, this new measure is only mildly correlated with other commonly used uncertainty proxies. However, when ordered last in a VAR system that includes the aggregate return on equity, the identified uncertainty shocks have large and persistent effects on economic activity.

To the best of our knowledge, there are only two studies that jointly analyze financial and uncertainty shocks in the VAR context. Focusing on the German economy, Popescu and Smets (2010) identify financial and uncertainty shocks using a recursive ordering, in which the uncertainty proxy is placed after the macro block but before the financial market risk index. In other words, they allow uncertainty shocks to elicit an immediate change in financial conditions but not vice versa. Under their identifying assumptions, uncertainty shocks have a small and temporary effects on output and financial risk premia, whereas financial disturbances have a considerably more persistent effect on economic activity.

In light of such restrictive assumptions, Gilchrist et al. (2014b) explore the macroeconomic implications of uncertainty and financial shocks using alternative orderings for the uncertainty and financial stress proxies.[7] Their first identification scheme posits that uncertainty shocks have an

[5] Although the use of dispersion indexes of expectations—an indication of the degree of disagreement among the survey participants—as a measure of uncertainty has a long tradition in the literature on inflation expectations and inflation uncertainty, this interpretation is not without controversy. In particular, using the individual probabilistic responses from the Survey of Professional Forecasters, D'Amico and Orphanides (2008) show that the disagreement about the mean forecast can be a poor proxy for the actual forecast uncertainty.

[6] Using a weighted-average of realized volatilities across different financial assets and countries as a measure of global uncertainty, Cesa-Bianchi et al. (2014) reach a similar conclusion in a Global VAR (GVAR) framework.

[7] The measure of uncertainty used by Gilchrist et al. (2014b) is based on the volatility of equity returns that have been purged of forecastable variation using a standard empirical asset pricing model. As a result, their uncertainty

immediate impact on the short-term policy rate and corporate bond credit spreads—an indicator of financial market strains—but they affect economic activity and inflation with a lag. In the second scheme, they reverse the ordering of the uncertainty proxy and credit spreads, which allows them to gauge the role of uncertainty shocks conditional on the current state of conditions in credit markets.

The key finding that emerges from their analysis is that the economic significance of uncertainty shocks hinges crucially on whether they have been orthogonalized with respect to the contemporaneous information in credit spreads. This knife-edge result, however, does not apply to financial disturbances identified vis-à-vis unanticipated increases in credit spreads: Under both sets of identifying assumptions, innovations in credit spreads induce a persistent and prolonged decline in the cyclically sensitive components of aggregate output; moreover, in the second scheme, they also elicit a significant increase in uncertainty upon impact.

The implications of these results are twofold. First, they point to distortions in financial markets as an important conduit through which uncertainty shocks can affect macroeconomic outcomes. The fact that uncertainty jumps immediately in response to an adverse credit shock suggest that fluctuations in uncertainty may arise endogenously in response to changes in broad financial market conditions. As noted above, an important goal of this paper is to relax the restrictive timing restrictions implicit in the identification schemes based on recursive ordering in order to analyze jointly the interaction behind changes in financial conditions and economic uncertainty and their effects on the macroeconomy. Using this new framework, we also provide a systematic comparison of the impact of uncertainty shocks across different uncertainty proxies, a useful and timely exercise given the plethora of uncertainty measures available to researchers.

The remainder of the paper is organized along the following lines. Section 3 presents an overview of the uncertainty proxies used in the analysis; it also examines the predictive content of the various proxies for monthly indicators of economic activity, conditional on the excess bond premium. Section 4 introduces the econometric methodology that allows us to explore the interplay of uncertainty and financial shocks without relying on the standard timing or sign restrictions. Section 5 presents the main results from our benchmark specification. In Section 6, we conduct an extensive sensitivity analysis of our main results. Section 7 concludes.

3 Uncertainty, Financial Conditions, and Economic Activity

3.1 Measuring Uncertainty and Financial Conditions

In spite of the intense interest in the role of uncertainty shocks as a source of macroeconomic fluctuations, there is little consensus among economists on what is the best measure of economic uncertainty. As a result, the empirical literature is awash with different uncertainty proxies and new measures crop up all the time. Rather than taking a stand on any particular indicator, we consider six different measures of uncertainty, which we judge span the range of methodological

proxy is less likely to reflect the countercyclical nature of informational and contractual frictions that have been theoretically linked to the countercyclical dispersion of stock returns, a popular measure of economic uncertainty.

Table 1: Selected Characteristics of Different Uncertainty Measures

	Summary Statistic					
Variable	CV	α_1	α_2	α_3	q_{LL}	RVN
RVOL[a]	0.60	0.70	0.14	0.03	−11.14	3.50***
IVOL[b]	0.38	0.64	0.18	0.05	−18.85*	0.08
VXO[c]	0.40	0.83	−0.00	0.04	−16.74	2.25**
BBD[d]	0.31	0.84	0.06	0.12	−13.65	0.66
BES[e]	0.14	0.80	0.26	0.05	−18.22*	−0.12
SCOT[f]	0.39	0.53	0.03	0.07	−15.03	1.18

	Pairwise Correlations					
Variable	RVOL	IVOL	VXO	BBD	BES	SCOT
RVOL	1.00	0.64***	0.84***	0.42***	0.13***	0.37***
IVOL		1.00	0.58***	0.26***	0.23***	0.26***
VXO			1.00	0.41***	0.19***	0.31***
BBD				1.00	−0.01	0.24***
BES					1.00	0.14**
SCOT						1.00

NOTE: The entries in the table denote the specified summary statistic: CV = coefficient of variation; α_k = partial autocorrelation at lag k; q_{LL} = the Elliott and Müller (2006) test statistic of the null hypothesis that the autoregressive coefficients from an AR(3) model are constant over time; and RVN = the Bartels (1982) test statistic of the null hypothesis that the OLS residuals from an AR(3) model are randomly distributed. * $p < .10$, ** $p < .05$, and *** $p < .01$.

[a] Realized equity volatility (1973:M1–2012:M12, $T = 480$).

[b] Idiosyncratic equity volatility based on Gilchrist et al. (2014b) (1973:M1–2012:M12, $T = 480$).

[c] Option-implied volatility on the S&P 100 stock futures index (1986:M1–2012:M12, $T = 324$).

[d] Uncertainty measure based on Baker et al. (2013) (1985:M1–2012:M12, $T = 336$).

[e] Uncertainty measure based on Bachmann et al. (2013) (1973:M1–2011:M12, $T = 468$).

[f] Uncertainty measure based on Scotti (2013) (1991:M1–2012:M12, $T = 264$).

approaches used to infer fluctuations in economic uncertainty.

We focus on measures available at a monthly frequency. Our benchmark proxy for economic uncertainty is the realized stock market volatility (**RVOL**), a measure that is simple to construct and is available over the longest time period. We also consider two other measures based on equity valuations: shocks to the idiosyncratic volatility of (excess) equity returns that are common to U.S. nonfinancial firms (**IVOL**), a measure proposed by Gilchrist et al. (2014b); and the option-implied volatility on the S&P 100 stock futures index constructed by the Chicago Board of Option Exchange (**VXO**).[8]

The remaining three proxies eschew financial market data. Specifically, our fourth proxy is the widely cited index of policy-related economic uncertainty developed by Baker et al. (2013) (**BBD**). The fifth proxy for macroeconomic uncertainty, put forth by Bachmann et al. (2013), is a measure

[8] We use the VXO, as opposed to the VIX option-implied volatility, because the VXO is available starting in January 1986, compared with January 1990, the starting date for the VIX. The correlation between these two indicators, however, is almost 0.99 at a monthly frequency.

of forecast dispersion constructed using the Philadelphia Fed's Business Outlook Survey (**BES**). And lastly, we also consider the real-time uncertainty index developed by Scotti (2013), who, using a dynamic factor model and "surprises" derived from economic data releases, infers how uncertain are financial market participants about the economic outlook (**SCOT**). (Details concerning the construction of the various uncertainty measures are contained in Appendix A.)

The top panel of Table 1 provides some summary statistics for the six uncertainty measures used in our analysis. Not too surprising, the coefficients of variation for the uncertainty proxies derived from equity valuations tend to be larger compared with those of uncertainty proxies that are not based on financial market data. As evidenced by the partial correlations, most of the measures exhibit significant positive first-order autocorrelation; the two exceptions are the IVOL and SCOT uncertainty proxies, which are governed by processes with much lower serial correlation. The degree of serial dependence, however, dies off very quickly in every case. Letting each series follow an AR(3) process, there appears to be little evidence of parameter instability in the autoregressive coefficients, according to the Elliott and Müller (2006) Quasi-Local Level test: Only for the IVOL and BES uncertainty measures, we reject—and only at the 10 percent significance level—the null hypothesis that the autoregressive coefficients are constant over time. Moreover, in most cases, the resulting residuals appear to be distributed randomly.

As shown by the entries in the bottom panel, the six series, in general, exhibit significant positive contemporaneous correlation. As expected, the highest degree of comovement is between the three uncertainty proxies based on the stock market data (RVOL, IVOL, and VXO). The other three measures (BBD, BES, and SCOT) are also positively correlated with their equity-based counterparts, though to a significantly lesser extent. The pairwise correlations between BBD, BES, and SCOT, in contrast, are notably smaller. In fact, the correlation between the BBD and BES proxies is statistically and economically indistinguishable from zero, while the correlation between the BES and SCOT measures, though positive, is quite low.

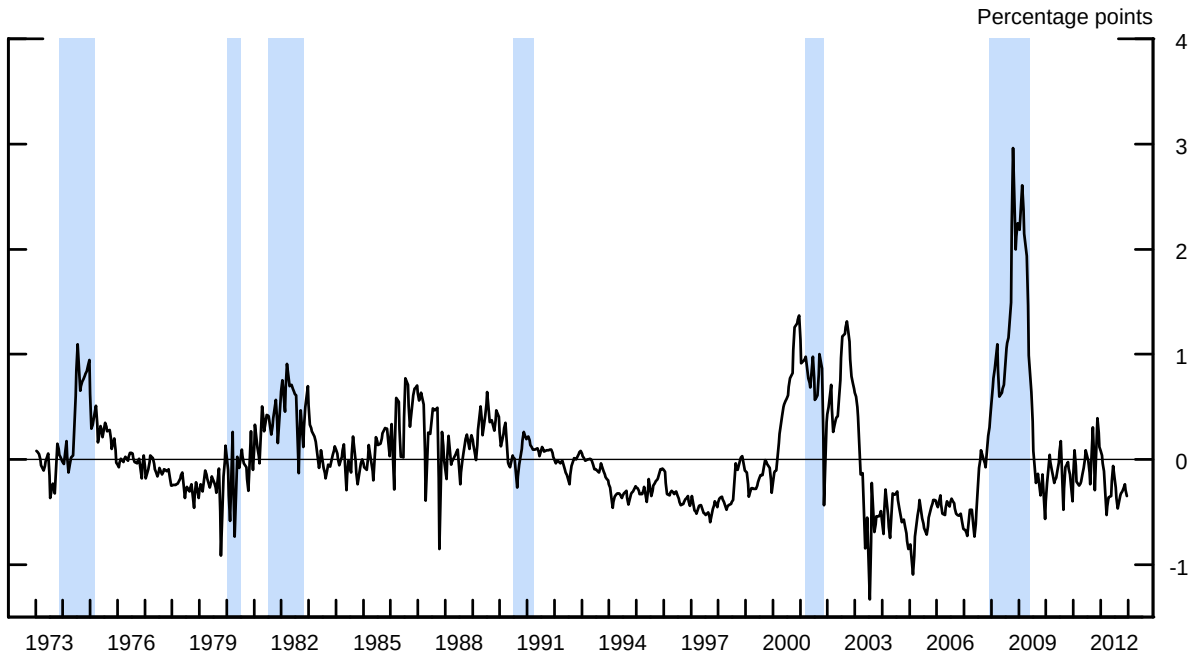
3.2 Measuring Financial Conditions

As discussed above, we rely on the information contained in corporate credit spreads to measure strains in financial markets. In particular, we use the excess bond premium, an estimate of the extra compensation demanded by bond investors for bearing exposure to U.S. nonfinancial corporate credit risk, above and beyond the compensation for expected losses. As emphasized by Gilchrist and Zakrajšek (2012), the U.S. corporate cash market is served by major financial institutions and fluctuations in the EBP thus capture shifts in the risk attitudes of these institutions and their willingness to bear credit risk and to intermediate credit more generally in global financial markets.[9]

Figure 2 shows this indicator of the effective "risk-bearing capacity" of the financial intermediary

[9]This interpretation is also supported by the empirical work of Adrian and Shin (2010) and Adrian et al. (2010a,b), who show that risk premiums in asset markets are very sensitive to movements in capital and balance sheet conditions of financial intermediaries. Theoretical foundations for such "intermediary" asset pricing theories are developed in the influential work of He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014).

Figure 2: The Excess Bond Premium



NOTE: Sample period: monthly data from 1973:M1 to 2012:M12. The solid line depicts the estimate of the excess bond premium, an indicator of the tightness of financial conditions (see Gilchrist and Zakrajšek, 2012). The shaded vertical bars denote the NBER-dated recessions.

sector over the 1973–2012 period. Note that the EBP appears to be a particularly timely indicator of strains in the financial system. As the intensifying downturn in the U.S. subprime mortgage market in the latter half of 2006 led to the emergence of significant strains in term funding markets in the United States and Europe during the summer of 2007, the EBP rose sharply, an increase concomitant with a jump in almost all measures of economic uncertainty. More generally, the pairwise correlation between the EBP and the six uncertainty proxies range from a low of 0.25 (BES) to a high of almost 0.70 (RVOL and VXO), underscoring the close relationship between changes in financial conditions and swings in economic uncertainty.

3.3 Uncertainty and Financial Conditions as Predictors of Economic Activity

To assess the relative predictive ability of uncertainty and financial conditions for economic activity, we first perform a simple forecasting exercise. Letting Y_t denote a monthly indicator of economic activity, we estimate the following univariate specification:

$$\Delta_h Y_{t+h} = \alpha + \beta_1 \sigma_t + \beta_2 \text{EBP}_t + \boldsymbol{\gamma}' \mathbf{Z}_t + \sum_{i=1}^{p} \rho_i \Delta Y_{t-i} + \epsilon_{t+h}, \tag{1}$$

where $\Delta_h Y_{t+h} \equiv \frac{1200}{h+1} \ln\left(\frac{Y_{t+h}}{Y_{t-1}}\right)$ and $h \geq 0$ is the forecast horizon ($\Delta_0 \equiv \Delta$). In the forecasting regression (1), σ_t denotes an uncertainty indicator in month t, EBP_t is the excess bond premium in the same month, $\mathbf{Z}_t$ is a vector of other financial indicators that may contain useful information about the economic outlook, and ϵ_{t+h} is the forecast error.[10]

Our baseline forecasting exercise abstracts from the information content of other financial indicators—that is, $\mathbf{Z}_t = \emptyset$. For each of the six uncertainty indicators, we estimate the resulting specification (1) separately by OLS. Measures of monthly economic activity considered include (manufacturing) industrial production and private (nonfarm) payroll employment. To facilitate the comparison of the predictive content of different uncertainty measures and the EBP, we report the standardized estimates of the coefficients β_1 and β_2. The results for the forecast horizon of 3 months are tabulated in panels A and B of Table 2, whereas those for the 12-month-ahead horizon are shown in panels C and D.[11]

According to Table 2, the predictive content of various uncertainty measures for economic activity is fairly uneven at the 3-month-ahead forecast horizon (panels A and B). While increases in the equity-based measures of economic uncertainty are generally associated with statistically and economically significant slowdown in the growth of industrial output and employment, the information content of the VXO is quite limited. Similarly, both the BBD policy uncertainty index and the SCOT index appear to be uninformative about the near-term course for economic activity. The survey-based BES uncertainty index, by contrast, is a robust predictor of the growth in both industrial output and employment—an increase of one standard deviation in the BES uncertainty index in month t is estimated to shave off about two percentage points in the (annualized) growth rate of industrial production over the subsequent three months and nearly three-quarters of a percentage point in the growth of nonfarm payroll employment.

In comparison with these uncertainty measures, the EBP appears to be a far more robust predictor of near-term economic developments. Moreover, the magnitude of the estimated coefficients implies an economically significant negative relationship between changes in financial conditions and future economic activity. For example, using a coefficient estimate of 0.35, a value in the range of the central tendency of the point estimates reported in panel A, an increase of 50 basis points in the EBP in month t (about one standard deviation) implies a 2.5 percentage points (annualized) drop in the growth rate of industrial output over the subsequent three months.

The uneven forecasting performance of the uncertainty indicators is also evident at longer horizons (panels C and D). While increases in the RVOL, IVOL, and BES indicators continue to

[10] Note that the timing implied by this specification allows for the possibility of "nowcasting" (i.e., $h = 0$), and it is intended to capture the fact that when forecasting an indicator of economic activity in period t, economists, because of reporting lags, typically do not observe the current value of the indicator, while the financial indicators used to assess the current state of credit market conditions and most uncertainty indicators are readily available.

[11] To take into account the MA($h+1$) structure of the error term ϵ_{t+h} induced by overlapping observations, we compute the covariance matrix of the estimated parameters according to Hodrick (1992). As shown by Ang and Bekaert (2007), the standard errors developed by Hodrick (1992) retain the correct size even in relatively small samples when testing the null of no predictability in the context of overlapping observations. In all specifications, we set the lag length p in equation (1) equal to 6. All the results, however, are completely robust to both shorter ($p = 3$) and longer ($p = 12$) lag lengths.

Table 2: Uncertainty, Financial Conditions, and Economic Activity
(Baseline Specification)

Predictor	RVOL	IVOL	VXO	BBD	BES	SCOT
A. Industrial Production ($h = 3$ months)						
σ_t	−0.179	−0.111	−0.018	−0.031	−0.270	−0.068
	[4.59]	[3.57]	[0.38]	[0.81]	[7.28]	[1.54]
EBP_t	−0.278	−0.339	−0.401	−0.397	−0.368	−0.498
	[6.58]	[7.37]	[7.56]	[7.61]	[7.87]	[8.91]
Adj. R^2	0.352	0.341	0.467	0.457	0.398	0.536
B. Payroll Employment ($h = 3$ months)						
σ_t	−0.157	−0.130	−0.054	0.006	−0.210	−0.049
	[8.03]	[5.41]	[2.19]	[0.28]	[6.28]	[2.26]
EBP_t	−0.165	−0.216	−0.213	−0.235	−0.222	−0.337
	[6.93]	[8.58]	[7.11]	[7.52]	[8.58]	[9.77]
Adj. R^2	0.663	0.662	0.806	0.797	0.684	0.839
C. Industrial Production ($h = 12$ months)						
σ_t	−0.119	−0.055	0.041	0.121	−0.357	0.040
	[5.22]	[1.98]	[1.38]	[4.30]	[10.72]	[2.33]
EBP_t	−0.295	−0.340	−0.473	−0.483	−0.351	−0.550
	[8.58]	[9.69]	[11.21]	[11.21]	[9.95]	[12.10]
Adj. R^2	0.160	0.153	0.241	0.242	0.266	0.290
D. Payroll Employment ($h = 12$ months)						
σ_t	−0.164	−0.175	0.011	0.147	−0.349	0.037
	[11.77]	[8.68]	[0.57]	[9.19]	[11.67]	[3.57]
EBP_t	−0.251	−0.298	−0.330	−0.359	−0.299	−0.463
	[13.13]	[15.56]	[13.33]	[14.03]	[15.79]	[17.78]
Adj. R^2	0.420	0.429	0.602	0.606	0.503	0.644

NOTE: The dependent variable in each specification is $\Delta_h Y_{t+h}$, the annualized growth rate in the specified indicator of economic activity from month $t-1$ to month $t+h$. The entries in the row of the table corresponding to σ_t denote the standardized estimates of the OLS coefficients associated with the specified uncertainty indicator in month t: RVOL = realized equity volatility (1973:M1–2012:M12, $T = 480$); IVOL = idiosyncratic equity volatility based on Gilchrist et al. (2014b) (1973:M1–2012:M12, $T = 480$); VXO = option-implied volatility on the S&P 100 stock futures index (1986:M1–2012:M12, $T = 324$); BBD = uncertainty measure based on Baker et al. (2013) (1985:M1–2012:M12, $T = 336$); BES = uncertainty measure based on Bachmann et al. (2013) (1973:M1–2011:M12, $T = 468$); and SCOT = uncertainty measure based on Scotti (2013) (1991:M1–2012:M12, $T = 264$). The entries in the row of the table corresponding to EBP_t denote the standardized estimates of the OLS coefficients associated with the excess bond premium in month t, an indicator of the tightness of financial conditions (see Gilchrist and Zakrajšek, 2012). In addition to σ_t and EBP_t, each specification also includes a constant and 6 lags of ΔY_{t-1} (not reported). Absolute asymptotic t-statistics reported in brackets are computed according to Hodrick (1992).

signal a slowdown in economic activity, a rise in the BBD policy uncertainty index is associated with an economically and statistically significant acceleration in industrial production and a pickup in employment growth over the subsequent year. The same is true of the SCOT uncertainty index, though the magnitude of the estimated effect is economically negligible in that case. Movements in the EBP, in contrast, continue to provide unambiguous and informative signals about the evolution of the year-ahead economic outlook, with a tightening of financial conditions portending a marked deceleration in industrial output and a significant deterioration in labor market conditions.

Our next forecasting exercise examines the robustness of the above results by conditioning on other potentially useful information in financial markets. Specifically, in this alternative specification we let $\mathbf{Z}_t = [TS_t \ RR_t]'$, where TS_t denotes the "term spread" and RR_t is the real 2-year Treasury yield.[12] The results of this exercise are reported in Table 3. To conserve space, we report the results for $h = 12$ only, but the results for the shorter-term forecast horizons were qualitatively very similar.

As shown in panel A, the inclusion of the slope of the yield curve and the real short-term rate—two indicators of the stance of monetary policy—significantly improves the in-sample fit of the regression for the year-ahead growth in industrial production. For the specifications involving RVOL and IVOL, which are estimated over the longest sample period (1973:M1–2012:M12), the adjusted R^2 more than doubles; for the specifications estimated using data since the mid-1980s—those involving the BBD and VXO measures of uncertainty—the increase in the goodness-of-fit is not as large, though it is still substantial. While the term spread and the real short-term rate both contain significant predictive power for the year-ahead growth in industrial output, conditioning on these two financial indicators in no way affects the information content of the EBP. In contrast, the forecasting ability of the different uncertainty indicators, which was already uneven according to the baseline specification, diminishes notably for the most informative indicators (RVOL and BES).

A similar picture emerges when we look at the employment growth (panel B). The inclusion of the term spread and the real short-term rate in the predictor set yields sizable improvements in the in-sample fit, though not as pronounced as in the case of industrial production, a much more volatile measure of economic activity. The economic significance of the most informative uncertainty indicators—RVOL, IVOL, and BES, according to the baseline specification—tends to diminish somewhat with the inclusion of these two financial indicators, while the economic impact of the EBP is unaffected across all specification. Note that even conditional on this richer information set, increases in the BBD policy uncertainty index continue to signal a pickup in economic activity. Increases in the EBP, by contrast, continue to be unambiguously associated with a significant deterioration in the medium-term economic outlook.

The results from the above forecasting exercises—which, of course, are completely silent on

[12]The term spread is defined as the difference between the 3-month constant-maturity Treasury yield and the 10-year constant-maturity yield. The real 2-year Treasury yield is defined as the 2-year nominal Treasury yield in month t less realized inflation, where realized inflation is given by the log-difference between the core consumer price index in period $t-1$ and its lagged value a year earlier.

Table 3: Uncertainty, Financial Conditions, and Economic Activity
(Augmented Specification)

Predictor	RVOL	IVOL	VXO	BBD	BES	SCOT
A. Industrial Production ($h = 12$ months)						
σ_t	−0.048	−0.063	0.055	0.162	−0.241	−0.007
	[2.33]	[2.35]	[1.87]	[4.38]	[7.12]	[0.43]
EBP_t	−0.393	−0.402	−0.537	−0.559	−0.411	−0.541
	[11.97]	[11.94]	[12.88]	[12.40]	[12.18]	[12.76]
TS_t	0.417	0.421	0.357	0.299	0.342	0.361
	[11.03]	[11.34]	[11.44]	[9.53]	[8.53]	[10.78]
RR_t	0.222	0.226	0.400	0.432	0.240	0.413
	[5.45]	[5.56]	[8.82]	[9.38]	[6.09]	[8.86]
Adj. R^2	0.387	0.389	0.417	0.420	0.433	0.461
B. Payroll Employment ($h = 12$ months)						
σ_t	−0.125	−0.183	0.009	0.144	−0.269	0.000
	[8.60]	[9.02]	[0.46]	[7.27]	[9.03]	[0.04]
EBP_t	−0.277	−0.309	−0.347	−0.391	−0.316	−0.426
	[14.54]	[16.37]	[14.64]	[15.54]	[17.23]	[16.62]
TS_t	0.321	0.330	0.342	0.285	0.253	0.323
	[12.69]	[13.03]	[15.00]	[12.52]	[9.57]	[13.06]
RR_t	0.092	0.108	0.251	0.299	0.114	0.235
	[2.73]	[3.30]	[11.15]	[12.50]	[3.63]	[10.03]
Adj. R^2	0.529	0.550	0.711	0.716	0.576	0.732

NOTE: The dependent variable in each specification is $\Delta_{12}Y_{t+12}$, the annualized growth rate in the specified indicator of economic activity from month $t-1$ to month $t+12$. The entries in the row of the table corresponding to σ_t denote the standardized estimates of the OLS coefficients associated with the specified uncertainty indicator in month t: RVOL = realized equity volatility (1973:M1–2012:M12, $T = 480$); IVOL = idiosyncratic equity volatility based on Gilchrist et al. (2014b) (1973:M1–2012:M12, $T = 480$); VXO = option-implied volatility on the S&P 100 stock futures index (1986:M1–2012:M12, $T = 324$); BBD = policy uncertainty measure based on Baker et al. (2013) (1985:M1–2012:M12, $T = 336$); BES = uncertainty measure based on Bachmann et al. (2013) (1973:M1–2011:M12, $T = 468$); and SCOT = uncertainty measure based on Scotti (2013) (1991:M1–2012:M12, $T = 264$). The entries in the row of the table corresponding to EBP_t denote the standardized estimates of the OLS coefficients associated with the excess bond premium in month t, an indicator of the tightness of financial conditions (see Gilchrist and Zakrajšek, 2012). The entries in the rows of the table corresponding to TS_t and RR_t denote the standardized estimates of the OLS coefficients associated with the 3m/10y term spread and the real 2-year Treasury yield, respectively. In addition to σ_t, EBP_t, TS_t, and RR_t, each specification also includes a constant and 6 lags of ΔY_{t-1} (not reported). Absolute asymptotic t-statistics reported in brackets are computed according to Hodrick (1992).

the causal relationship between uncertainty, financial conditions, and economic activity—are instructive for two reasons. First, they underscore the fact that measures of financial distress based on corporate bond credit spreads are highly informative about the economic outlook. Second, although the information content of various uncertainty indicators appears to be somewhat mixed, the available evidence nevertheless suggests that some of these indicators contain economically and statistically significant marginal predictive power for economic activity. In combination with

the fact that episodes of financial distress are closely associated with periods of heightened economic uncertainty and that theoretical mechanisms based on frictions in financial markets imply an important interaction between changes in financial conditions and fluctuations in uncertainty, a natural question raised by this evidence concerns the relative importance of financial and uncertainty shocks in business cycle fluctuations. To answer this question empirically, however, one has to take a stand on the joint identification of these two types of shocks.

4 Identifying Uncertainty and Financial Shocks

To identify uncertainty and financial shocks, we employ the penalty function approach (PFA) proposed initially by Faust (1998) and Uhlig (2005) in the VAR-based identification of monetary policy shocks, an approach that was later extended by Mountford and Uhlig (2009) to jointly identify multiple structural disturbances. The PFA selects a structural VAR model by maximizing a criterion function subject to inequality constraints. The criterion function consists of the sum of impulse response functions (IRFs) of selected variables at horizons 0 to H, while the inequality constraints correspond to sign restrictions on these IRFs. In this section, we first provide a general formulation of the PFA. We then discuss the rationale underlying our two identification schemes—that is, the choice of the penalty functions—and the estimation details.

4.1 The SVAR and the Penalty Function

Consider the following SVAR:

$$\mathbf{y}_t'\mathbf{A}_0 = \sum_{i=1}^{p} \mathbf{y}_{t-i}'\mathbf{A}_i + \mathbf{c} + \boldsymbol{\epsilon}_t'; \quad t = 1, \ldots, T, \tag{2}$$

where $\mathbf{y}_t$ is an $n \times 1$ vector of endogenous variables, $\boldsymbol{\epsilon}_t$ is an $n \times 1$ vector of structural shocks, $\mathbf{A}_i$, $i = 1, \ldots, p$, is an $n \times n$ matrix of structural parameters with $\mathbf{A}_0$ invertible, $\mathbf{c}$ is a $1 \times n$ vector of parameters, p is the lag length, and T is the sample size. Conditional on past information and the initial conditions $\mathbf{y}_0, \ldots, \mathbf{y}_{1-p}$, the vector of structural shocks $\boldsymbol{\epsilon}_t$ is assumed to be Gaussian with mean zero and covariance matrix $\mathbf{I}_n$, the $n \times n$ identity matrix.

The SVAR model in equation (2) can be written more compactly as

$$\mathbf{y}_t'\mathbf{A}_0 = \mathbf{x}_t'\mathbf{A}_+ + \boldsymbol{\epsilon}_t', \tag{3}$$

where $\mathbf{A}_+' = \begin{bmatrix}\mathbf{A}_1' \ldots \mathbf{A}_p' & \mathbf{c}'\end{bmatrix}$ and $\mathbf{x}_t' = \begin{bmatrix}\mathbf{y}_{t-1}' \ldots \mathbf{y}_{t-p}' & \mathbf{1}\end{bmatrix}$. The dimension of $\mathbf{A}_+$ is $m \times n$, where $m = np + 1$, and the elements of matrices $\mathbf{A}_0$ and $\mathbf{A}_+$ correspond to the structural parameters of the VAR system. The reduced-form representation of the VAR is given by

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

where $\mathbf{B} = \mathbf{A}_+\mathbf{A}_0^{-1}$, $\mathbf{u}_t' = \boldsymbol{\epsilon}_t'\mathbf{A}_0^{-1}$, and $\mathbb{E}\big[\mathbf{u}_t\mathbf{u}_t'\big] = \big(\mathbf{A}_0\mathbf{A}_0'\big)^{-1} \equiv \boldsymbol{\Sigma}$; the matrices $\mathbf{B}$ and $\boldsymbol{\Sigma}$ are the reduced-form parameters. In this context, the impulse response functions are defined as follows:

Definition 1 *Let $\{\mathbf{A}_0, \mathbf{A}_+\}$ represent arbitrary structural parameters. Then, the IRF of the i-th variable to the j-th structural shock at a finite horizon h—denoted by $\mathbf{L}_h(\mathbf{A}_0, \mathbf{A}_+)_{ij}$—corresponds to the element in row i and column j of the matrix $\big[\mathbf{A}_0^{-1}\mathbf{J}'\mathbf{F}^h\mathbf{J}\big]'$, where*

$$\mathbf{F} = \begin{bmatrix} \mathbf{A}_1\mathbf{A}_0^{-1} & \mathbf{I}_n & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{A}_{p-1}\mathbf{A}_0^{-1} & \mathbf{0} & \cdots & \mathbf{I}_n \\ \mathbf{A}_p\mathbf{A}_0^{-1} & \mathbf{0} & \cdots & \mathbf{0} \end{bmatrix} \quad \textit{and} \quad \mathbf{J} = \begin{bmatrix} \mathbf{I}_n \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{bmatrix}.$$

Note that the matrix of IRFs upon impact is given by $\mathbf{L}_0\big(\mathbf{A}_0, \mathbf{A}_+\big) = \mathbf{A}_0^{-1}$. As in Uhlig (2005), we characterize the set of all possible IRFs using an $n \times n$ orthonormal matrix $\mathbf{Q} \in \mathscr{O}(n)$, where $\mathscr{O}(n)$ denotes the set of all orthonormal $n \times n$ matrices. To see this, let $\mathbf{T}$ denote the lower triangular matrix from the Cholesky factorization of $\boldsymbol{\Sigma}$. Then for any orthonormal matrix $\mathbf{Q}$, the matrix $\tilde{\mathbf{A}}_0^{-1} = \mathbf{TQ}$ is also a decomposition of $\boldsymbol{\Sigma}$ that satisfies $\big[\tilde{\mathbf{A}}_0\tilde{\mathbf{A}}_0'\big]^{-1} = \boldsymbol{\Sigma}$. Identification of the SVAR thus amounts to specifying a set of restrictions on the matrix $\mathbf{Q}$. For instance, $\mathbf{Q} = \mathbf{I}_n$ imposes identification based on the recursive ordering of the VAR (i.e., the widely used Cholesky decomposition), while sign restrictions on the IRFs involve specifying a set of admissible $\mathbf{Q}$ matrices.

It is worth emphasizing that our identification strategy does not identify all n structural shocks—that is, the entire $\mathbf{Q}$ matrix. Rather, we identify a subset $k \leq n$ of shocks, represented by $\mathbf{q}_j = \mathbf{Q}\mathbf{e}_j$, $j = 1, ..., k$, where $\mathbf{e}_j$ denotes the j-th column of $\mathbf{I}_n$. Specifically, let $\{\mathbf{A}_0, \mathbf{A}_+\}$ be any draw of the structural parameters and consider a case where the identification of the j-th structural shock restricts the IRF of a set of variables indexed by $I_j^+ \subset \{0, 1, \ldots, n\}$ to be positive and the IRF of a set of variables indexed by $I_j^- \subset \{0, 1, \ldots, n\}$ to be negative. Furthermore, assume that the restrictions on variable i are enforced for $H \geq 0$ periods. The identification of $\mathbf{q}_j$ then amounts to solving the following optimization problem:

$$\begin{aligned} \mathbf{q}_j^* &= \underset{\mathbf{q}_j}{\arg\min}\ \Psi(\mathbf{q}_j) && (4) \\ \text{s. t.} & \\ \mathbf{e}_i'\mathbf{L}_h(\mathbf{T}^{-1}, \mathbf{BT}^{-1})\mathbf{q}_j &> 0, \quad i \in I_j^+ \text{ and } h = 0, \ldots, H; && (5) \\ \mathbf{e}_i'\mathbf{L}_h(\mathbf{T}^{-1}, \mathbf{BT}^{-1})\mathbf{q}_j &< 0, \quad i \in I_j^- \text{ and } h = 0, \ldots, H; && (6) \\ \mathbf{Q}_{j-1}^{*\prime}\mathbf{q}_j &= 0, && (7) \end{aligned}$$

where

$$\Psi(\mathbf{q}_j) = \sum_{i \in I_j^+}\sum_{h=0}^{H}\left(-\frac{\mathbf{e}_i'\mathbf{L}_h(\mathbf{T}^{-1}, \mathbf{BT}^{-1})\mathbf{q}_j}{\sigma_i}\right) + \sum_{i \in I_j^-}\sum_{h=0}^{H}\left(\frac{\mathbf{e}_i'\mathbf{L}_h(\mathbf{T}^{-1}, \mathbf{BT}^{-1})\mathbf{q}_j}{\sigma_i}\right), \quad (8)$$

σ_i is the standard deviation of variable i, and $\mathbf{Q}_{j-1}^* = \left[\mathbf{q}_1^* \dots \mathbf{q}_{j-1}^*\right]$, for $j = 1, \dots, n$.[13]

In line with the existing literature, our characterization of the penalty function (8) assumes that the vector $\mathbf{q}_j$ rotates the IRFs associated with the Cholesky factor matrix $\mathbf{T}$. As in Uhlig (2005) and Mountford and Uhlig (2009), the constraints (5) and (6) correspond to sign restrictions on the IRFs that enter the penalty function $\Psi(\mathbf{q}_j)$. Note that the PFA selects a unique rotation matrix $\mathbf{Q}^*$ for each draw of the structural parameters $\{\mathbf{A}_0, \mathbf{A}_+\}$, the same as in the standard point identification. However, the PFA differs from the standard sign restrictions approach because the IRFs corresponding to each draw of the structural parameters $\{\mathbf{A}_0, \mathbf{A}_+\}$ are computed using the rotation matrix $\mathbf{Q}^*$ that minimizes the penalty function (8). The constraints 5 and 6 do not identify a set of structural models—that is, a set of $\mathbf{Q}$ matrices—rather, they define a set of admissible rotation matrices from which the $\mathbf{Q}^*$ is selected. In our implementation of the PFA, however, the sign restrictions are never violated, and the rotation matrix $\mathbf{Q}^*$ always lies in the interior of the admissible set.

Following Mountford and Uhlig (2009), we jointly identify multiple structural shocks sequentially by specifying a penalty function (8) for each shock and then imposing—via the constraint (7) in the optimization problem (4)—that shock j is orthogonal to shocks $1, \dots, j-1$. This sequential approach is reminiscent of a recursive ordering implicit in the Cholesky decomposition—in fact, this approach returns a Cholesky factorization of $\mathbf{\Sigma}$ if the penalty function that identifies shock j contains only the impact response ($H = 0$) of variable j, for $j = 1, \dots, n$. In all other cases, the sequential identification of the shocks using the PFA does not impose any zero restrictions on the structural parameters $\{\mathbf{A}_0, \mathbf{A}_+\}$ or on the IRFs at any horizon.

This identification strategy, however, is not invariant to the ordering of the shocks. Next we describe the two identification schemes used in our analysis, which share the same penalty functions and differ only in the ordering of the uncertainty and financial shocks. For the purpose of describing the two identification schemes, it suffices to say that without loss of generality, we order the EBP and an uncertainty measure first and second, respectively, in the vector of the endogenous variables $\mathbf{y}_t$.

4.2 Identification and Estimation

Our baseline identification scheme involves two restrictions. First, a financial shock corresponds to an innovation that generates the *largest increase* in the EBP for the first six months. The penalty function associated with this shock is given by

$$\Psi(\mathbf{q}_1) = \sum_{h=0}^{5} \left(-\frac{\mathbf{e}_1' \mathbf{L}_h(\mathbf{T}^{-1}, \mathbf{B}\mathbf{T}^{-1})\mathbf{q}_1}{\sigma_1} \right),$$

with

$$\mathbf{e}_1' \mathbf{L}_h(\mathbf{T}^{-1}, \mathbf{B}\mathbf{T}^{-1})\mathbf{q}_1 > 0, \quad h = 0, \dots, 5,$$

[13] We follow the convention by letting $\mathbf{Q}_0^*$ equal the $n \times n$ null matrix; to obtain σ_i, we compute the standard deviation of the OLS residuals associated with the i-th variable.

where $j = 1$ because we identify the first shock in the system; $i = 1$ because the EBP is the first variable in the system; $I_1^+ = \{1\}$ and $I_1^- = \emptyset$ because we only impose positive restrictions on the EBP; and $H = 5$ because we restrict the IRFs of the EBP for six month (in our notation the impact response occurs in period 0).

The second restriction identifies uncertainty shocks. Specifically, an uncertainty shock is an innovation that generates the *largest increase* in a measure of uncertainty for the first six months and is orthogonal to the financial disturbance identified by the first restriction. The penalty function associated with this shock is given by

$$\Psi(\mathbf{q}_2) = \sum_{h=0}^{5} \left(-\frac{\mathbf{e}_2' \mathbf{L}_h(\mathbf{T}^{-1}, \mathbf{B}\mathbf{T}^{-1})\mathbf{q}_2}{\sigma_2} \right),$$

with

$$\begin{aligned} \mathbf{e}_2' \mathbf{L}_h(\mathbf{T}^{-1}, \mathbf{B}\mathbf{T}^{-1})\mathbf{q}_2 &> 0, \quad h = 0, \ldots, 5; \\ \mathbf{Q}_1^{*\prime} \mathbf{q}_2 &= 0, \end{aligned}$$

where $j = 2$ because we are identifying the second shock and $i = 2$ because uncertainty is the second variable in the VAR.

Implicit in this identification scheme is an economically plausible argument that an unanticipated worsening in financial conditions is due primarily to an adverse financial shock, while the exogenous fluctuations in economic uncertainty are driven mainly by uncertainty shocks. Importantly, these identifying assumptions do not rule out the possibility that economic uncertainty might react contemporaneously to a change in financial conditions induced by a financial shock; by the same token, financial conditions are allowed to change with the impact of an uncertainty shock.

Although more general than the identification strategy based on the recursive ordering of the VAR system, our baseline identification scheme still imposes a particular form of a timing restriction—namely, the optimization problem that identifies the uncertainty shock is solved conditional on solving the optimization that identifies the financial shock. Given the close relationship between changes in financial conditions and swings in economic uncertainty, this sequential ordering may lead to a concern that the identified financial shocks are to some extent contaminated by uncertainty shocks.

To take into account this possibility, our alternative identification scheme reverses the ordering of the two optimization problems. In other words, we first identify an uncertainty shock as an innovation that generates the largest increase in the uncertainty indicator for the first six months after its impact. In the second step, a financial shock—orthogonal to the uncertainty shock implied by the first step—is identified as shock that induces the largest increase in the EBP for the first six months after its impact. We readily acknowledge that neither scheme fully resolves this thorny identification problem. However, in the absence of valid external instruments, we view the two approaches as providing useful bounds on the role of uncertainty and financial shocks in business

cycle fluctuations.

In spirit, our implementation of the PFA is similar to the identification strategy used by Uhlig (2003), Barsky and Sims (2011), and Kurmann and Otrok (2013), all of whom identify structural shocks by maximizing—over a pre-specified forecast horizon—the shock's contribution to the forecast error variance of a given variable. Our identification scheme, in contrast, identifies shocks by maximizing the impulse response of a given variable over a pre-specified horizon. We chose this approach because it implies that the identified financial shocks generate a persistent increase in the EBP—a period of financial distress—while uncertainty shocks lead to a persistent increase in an uncertainty proxy, that is, a period of heightened uncertainty. Selecting shocks that maximize the forecast error variance of these two variables, by contrast, does not guarantee that the their IRFs will not switch signs over the forecast horizon. However, the results reported below indicate that the two shocks identified using the PFA also explain a large fraction of the forecast error variance of their respective variables at business cycle frequencies, which suggests that the two approaches are unlikely to yield very different conclusions.

To implement the two identification schemes, we employ Bayesian estimation techniques. The benchmark monthly VAR specification consists of nine endogenous variables: (1) the EBP; (2) the RVOL uncertainty indicator; (3) the log of manufacturing industrial production; (4) the log of private (nonfarm) payroll employment; (5) the log of (real) personal consumption expenditures (PCE); (6) the log of the PCE price deflator; (7) the effective nominal federal funds rate; (8) the nominal 10-year Treasury yield; and (9) the value-weighted total stock market (log) return. We impose a Minnesota prior on the reduced-form VAR parameters by using dummy observations (see Del Negro and Schorfheide, 2011) and select the hyper-parameters that govern their prior distributions and the VAR lag length p by maximizing the marginal data density; to perform this optimization, we use the version of the CMA-ES evolutionary algorithm proposed by Andreasen (2010). The resulting specification, which includes a constant, is estimated over the 1975:M1–2012:M12 period using twelve lags of the endogenous variables.[14]

5 Main Results

This section presents our main results. First, we discuss the responses of macroeconomic variables to the identified financial and uncertainty shocks and the associated forecast error variance decompositions. In presenting these (and other similar) results, we adopt the following expositional scheme, which is best viewed in color. Specifically, the results based on the baseline identification of financial and uncertainty shocks use an orange-based color motif, with solid lines denoting implications of financial (EBP) shocks and dotted lines denoting implications of uncertainty (RVOL) shocks. The results based on the alternative identification of these two shocks use a green-based

[14] We use the first two years of the sample (1973:M1–1974:M12) as a training sample for the Minnesota prior. All the results reported in the paper are based on 10,000 draws from the posterior distribution of the structural parameters, where the first 2,000 draws were used as a burn-in period (increasing the number of draws had no effect on the reported results).

color motif, with solid lines denoting implications of uncertainty shocks and dotted lines denoting implications of financial shocks. In other words, the solid (dotted) lines are always referencing the implications of a shock that is identified first (second) in both identification schemes.

Our next set of results examines the historical contributions of financial and uncertainty shocks to U.S. economic fluctuations since the mid-1970s. Lastly, we corroborate our interpretation of the identified innovations as financial and uncertainty shocks by examining their correlations with other widely studied macroeconomic disturbances.

5.1 Macroeconomic Implications of Financial and Uncertainty Shocks

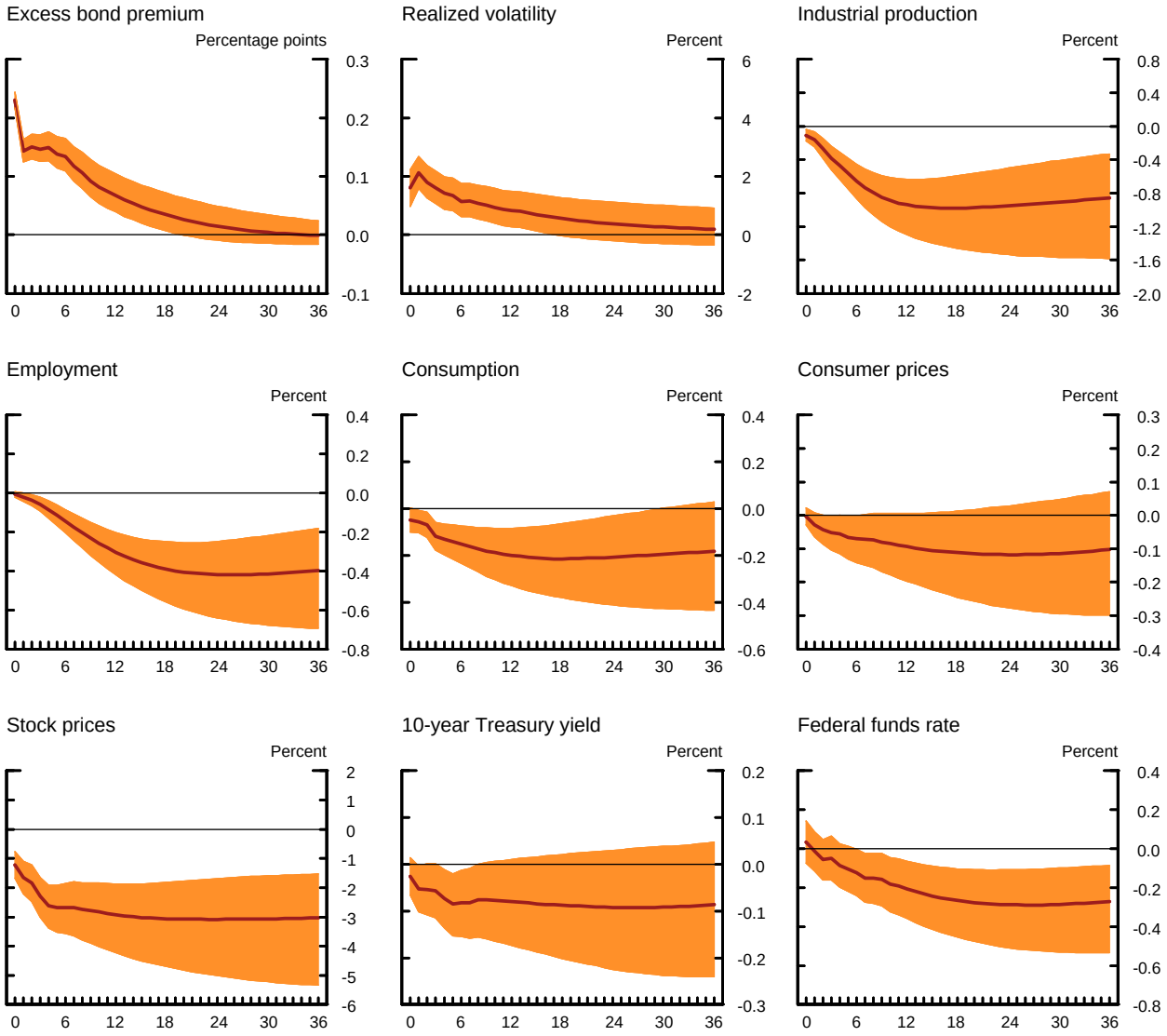
The solid lines in Figure 3 show the median impulse responses of the nine endogenous variables to a one standard deviation shock to the EBP under the baseline identification scheme, while the shaded bands represent the corresponding 90-percent pointwise credible bands. Overall, such an unanticipated jump in the EBP—only about 25 basis points—elicits an immediate increase in the RVOL measure of uncertainty and induces a significant deterioration in broad macroeconomic conditions. The fact that RVOL increases immediately in response to a rise in the EBP suggests that fluctuations in uncertainty may arise endogenously in response to changes in broader financial conditions.

On the real side, industrial production, an especially cyclically sensitive measure of economic activity, responds very quickly to the tightening of financial conditions and bottoms out a full percent below the trend about 14 months after the shock. The deterioration in labor market condition, while substantial, is a bit more gradual, with payroll employment reaching a trough about two years after the initial financial disruption. The ensuing labor market weakness is associated with a significant pullback in household spending, and the emergence of substantial and persistent economic slack induces a notable downward pressure on consumer prices. The prolonged slump engendered by an adverse financial shock is consistent with the growing empirical evidence, which shows that recoveries after "financial" recessions tend to be considerably more sluggish compared with "normal" recessions (see Cerra and Saxena, 2008; Reinhart and Rogoff, 2009; Bordo and Haubrich, 2010; Jorda et al., 2013).

On the financial side, the tightening of credit conditions and a rise in uncertainty lead to a sharp and immediate drop in the broad stock market, implying a substantial loss of wealth for the household sector that further saps consumer spending. The combination of growing economic slack and appreciable disinflation in the wake of the financial shock elicits a significant easing of monetary policy, as evidenced by the decline in the federal funds rate. And although longer-term interest rates decline noticeably in anticipation of such policy easing, the financial shock leaves stock prices permanently lower.

Figure 4 traces out the effects of a financial shock under the alternative identification scheme. In this case, an unanticipated increase in the EBP—again roughly about 25 basis points—has no meaningful economic or statistical effect on the RVOL measure of uncertainty. Nevertheless, the shock retains its hallmark features of a significant financial disruption. Factory output, employment,

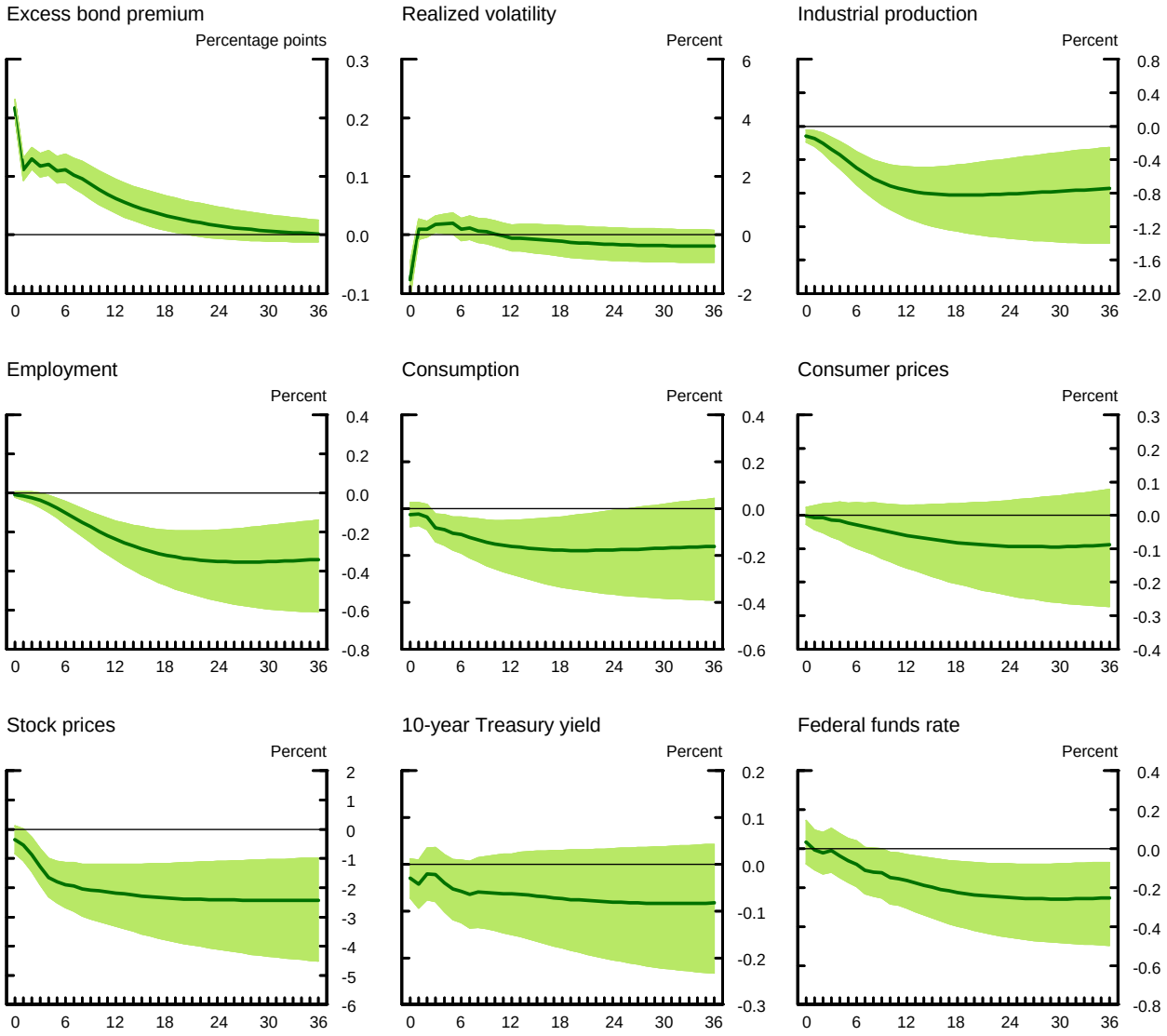
Figure 3: Macroeconomic Impact of a Financial Shock
(Baseline Identification Scheme)



NOTE: The solid line in each panel depicts the median impulse response of the specified variable to a 1 standard deviation shock to the EBP identified using the baseline identification scheme (see the text for details). Shaded bands denote the 90-percent pointwise credible sets.

and consumer spending all register substantial and persistent decline in response to an adverse financial shock, and the downturn in economic activity is amplified importantly by the substantial drop in the stock market. In fact, the magnitude and shape of the responses of all macroeconomic variables to the EBP shock under the alternative identification scheme are very similar to those implied by the baseline identification scheme shown in Figure 3. In combination, these results indicate that swings in uncertainty may not be very informative for gauging the macroeconomic effects of financial disturbances; at the same time, however, strains in credit markets will—in

Figure 4: Macroeconomic Impact of a Financial Shock
(Alternative Identification Scheme)

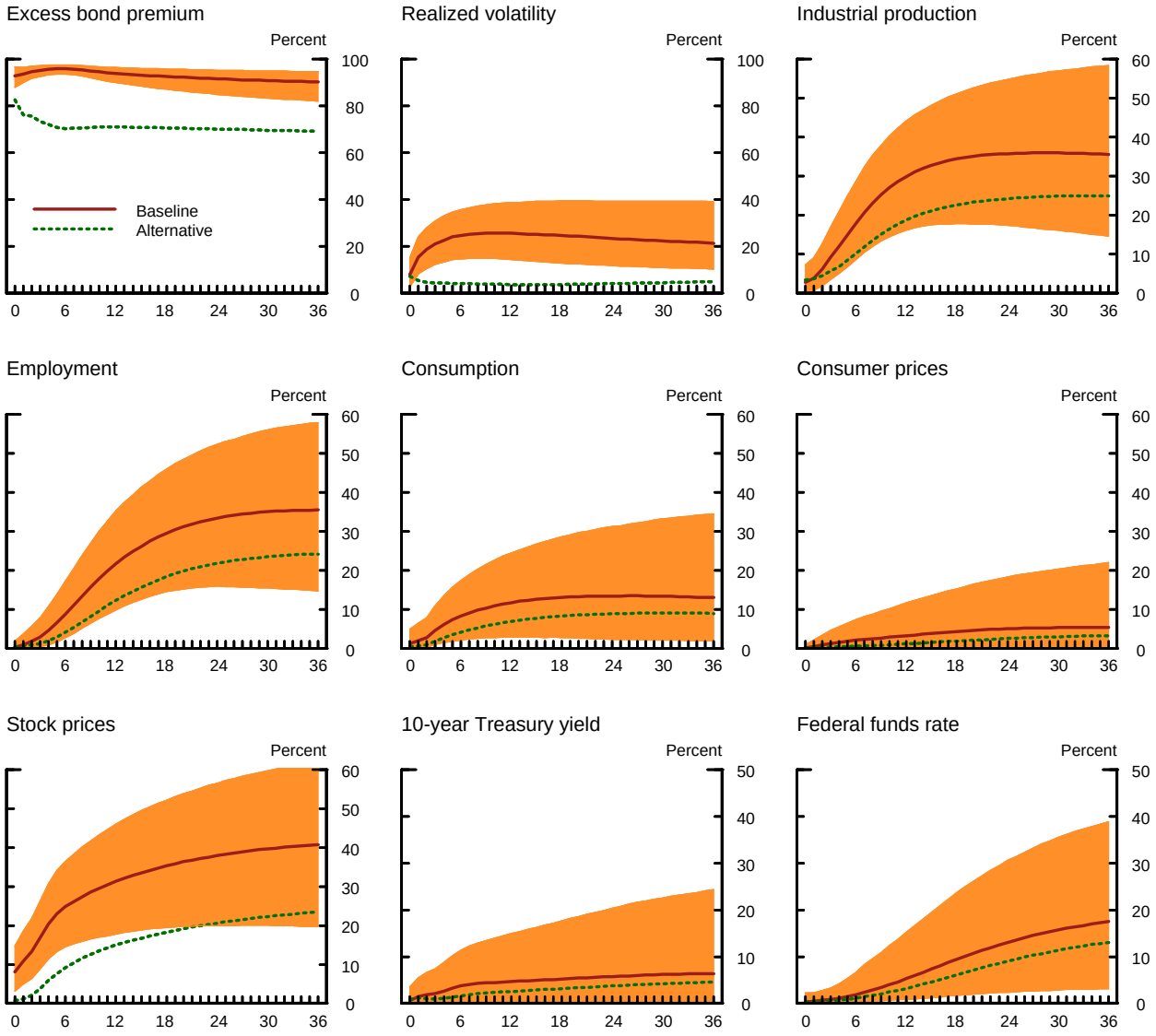


NOTE: The solid line in each panel depicts the median impulse response of the specified variable to a 1 standard deviation shock to the EBP identified using the alternative identification scheme (see the text for details). Shaded bands denote the 90-percent pointwise credible sets.

addition to depressing economic growth—likely lead to heightened economic uncertainty.

The solid lines in Figure 5 show the amount of variation in the same endogenous variables explained by financial shocks identified according to the first scheme, whereas the dotted lines show the same information for shocks implied by the alternative identification scheme. In both cases, the identification of financial shocks involved selecting orthogonalized innovations in the EBP that maximized the response of this indicator of the tightness of financial conditions over the first six months after the impact of the shock. However, under both approaches, the results

Figure 5: Forecast Error Variance Decomposition of a Financial Shock
(Baseline vs. Alternative Identification Scheme)



NOTE: The solid (dotted) line in each panel depicts the median estimate of the portion of the forecast error variance of a specified variable attributable to a 1 standard deviation shock to the EBP under the baseline (alternative) identification scheme (see the text for details). Shaded bands denote the 90-percent pointwise credible sets corresponding to the baseline identification scheme.

also imply that the identified financial shocks account for the bulk of the variation in the EBP at business cycle frequencies, a result consistent with the notion that exogenous changes in financial conditions are due primarily to financial disturbances. Consistent with the idea that fluctuations in uncertainty are partly a reflection of changes in the underlying financial conditions, innovations in the EBP implied by the baseline identification scheme explain a sizable portion of the forecast error variance in the RVOL measure of uncertainty. Under the alternative identification scheme, by contrast, financial shocks are completely uninformative about the future swings in uncertainty,

a result consistent with the impulse response shown in Figure 4.

According to this metric, financial shocks are a significant source macroeconomic fluctuations—they are estimated to explain between 25 and 35 percent of the variation in industrial production and payroll employment, and about 10 percent of the variation in consumer spending. In addition, such disruptions in the credit-intermediation process explain a significant portion of the variation in the stock market and short-term nominal interest rates. Overall, these proportions are in line with the recent evidence on the importance of credit shocks for business cycle fluctuations (see Gilchrist et al., 2009; Helbling et al., 2011; Meeks, 2012; Bassett et al., 2014a; Peersman and Wagner, 2014).

The macroeconomic implications of uncertainty shocks are shown in Figures 6 and 7. As evidenced by the response of the EBP, an unanticipated increase in financial market volatility of 1 standard deviation—about 5 percent—leads to an immediate tightening in credit market conditions under the alternative identification scheme (Figure 6). The uncertainty shock also has significant adverse consequences for economic activity: Factory output, payroll employment, and personal consumption expenditures all decline noticeably, though their respective declines in response to a positive uncertainty shock are somewhat less pronounced and persistent than in the case when the economy is hit by an adverse financial shock.

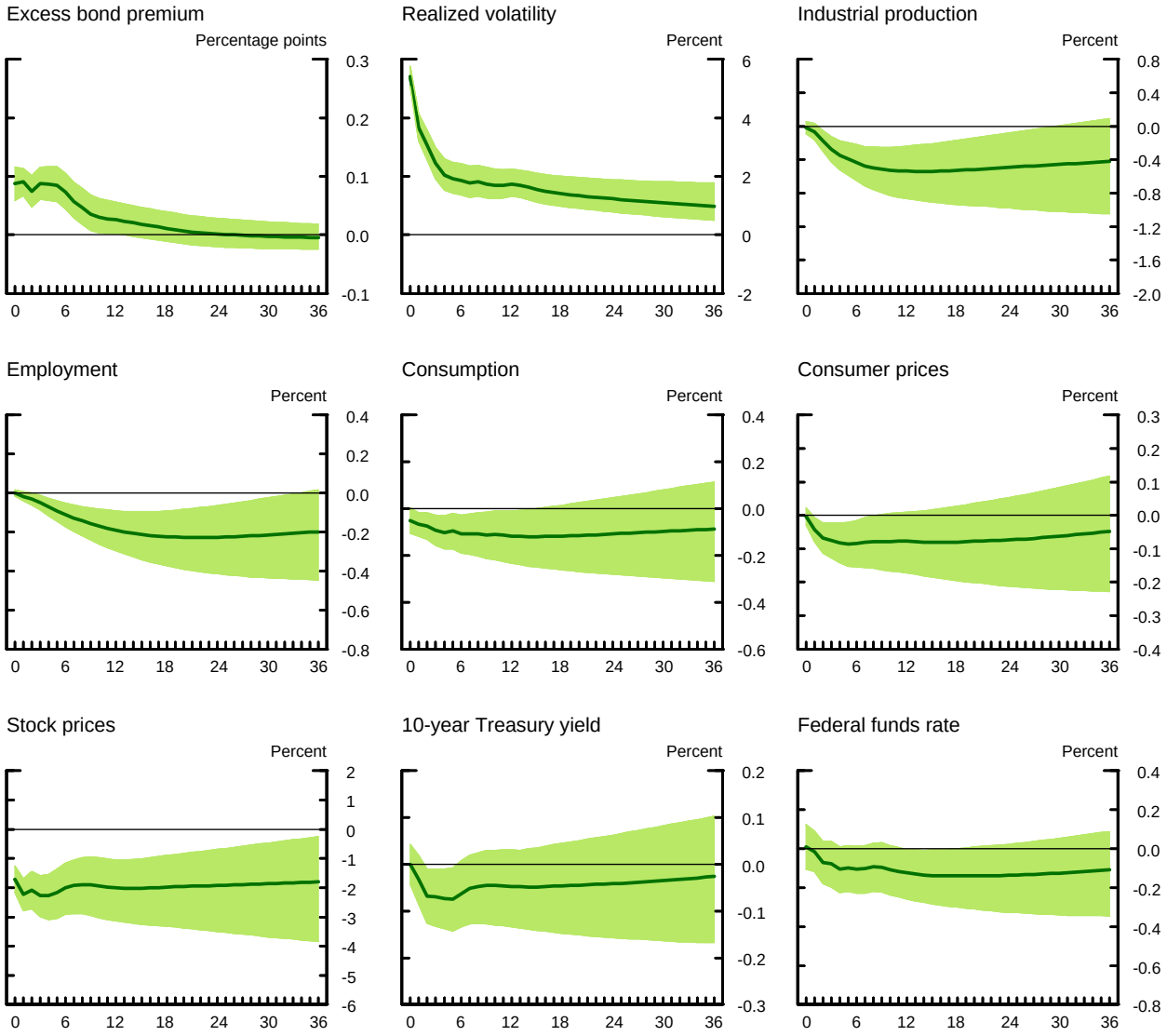
The qualitative similarity between uncertainty and financial shocks is also echoed in the behavior of the stock market, which drops sharply in response to a jump in uncertainty. As in the case of a financial disruption, share prices remain depressed for a considerable period of time, and the broad-based deterioration in economic conditions elicits as significant easing of monetary policy. The fact that the response of key macroeconomic variables to a financial shock is qualitatively so similar to that of an uncertainty shock underscores the difficulty of assigning distinct sign restrictions to the IRFs in order to jointly identify the two types of disturbances.

Figure 7 shows the implications of a positive uncertainty shock identified using the baseline scheme, in which the optimization problem that selects the financial shock is solved before the problem that identifies the orthogonalized volatility innovation. The sole effect of such an uncertainty shock, which is quite persistent, appears to be a short-lived decline in the stock market that has no consequences for broad financial conditions or real economic outcomes.[15] These results indicate that if uncertainty shocks are to have real economic effects, they must exert a significant independent effect on financial market conditions. And even though our identification schemes do not impose any zero restrictions on contemporaneous responses, identifying financial shocks first effectively shuts down this transmission channel.

The limited economic significance of uncertainty shocks in the baseline identification is corroborated by the dotted lines in Figure 8, which depict the contribution of such shocks to the forecast error variance of the endogenous variables of the VAR system. While uncertainty shocks implied

[15]The highly persistent response of realized volatility appears to be due to our parametrization of the Minnesota prior, rather than to some underlying economic mechanism. In fact, when we used a "weaker" parametrization of the prior, the response of RVOL converges to its mean within 12 months, while the responses of all other variables remain qualitatively and quantitatively very similar to those reported in Figure 7.

Figure 6: Macroeconomic Impact of an Uncertainty Shock
(Alternative Identification)

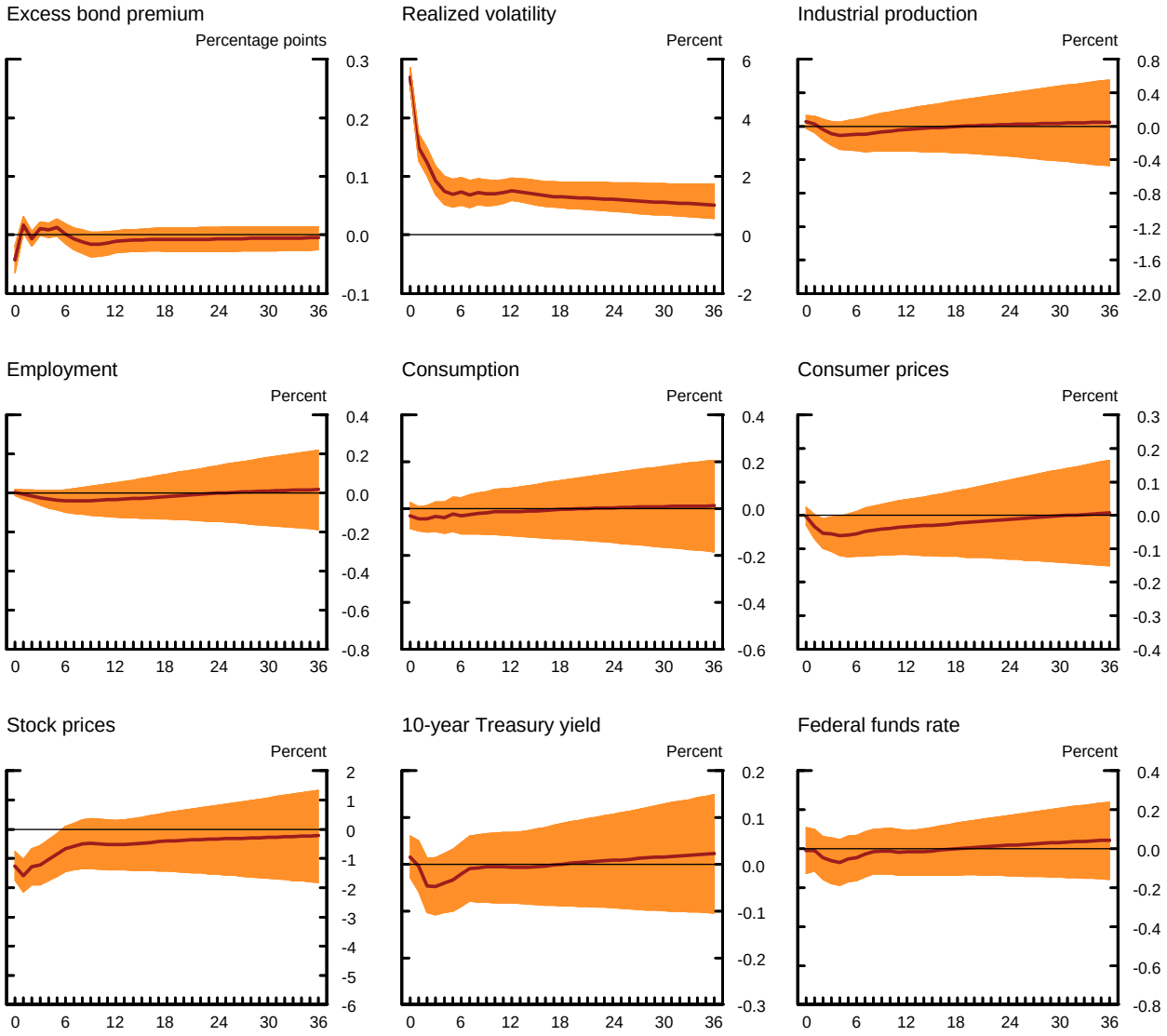


NOTE: The solid line in each panel depicts the median impulse response of the specified variable to a 1 standard deviation shock to the RVOL uncertainty measure identified using the alternative identification scheme (see the text for details). Shaded bands denote the 90-percent pointwise credible sets.

by the baseline identification scheme explain a significant majority of the variability in the RVOL measure of uncertainty, their contribution to the forecast error variance of other variables—with the exception of the stock market—is indistinguishable from zero. Even under the alternative identification scheme, the significance of uncertainty shocks is, judging by this metric, considerably smaller than than of financial shocks under either identification scheme.

In combination, these results are consistent with theoretical mechanisms that emphasize the presence of frictions in financial markets—and their effect on the effective supply on credit—as an

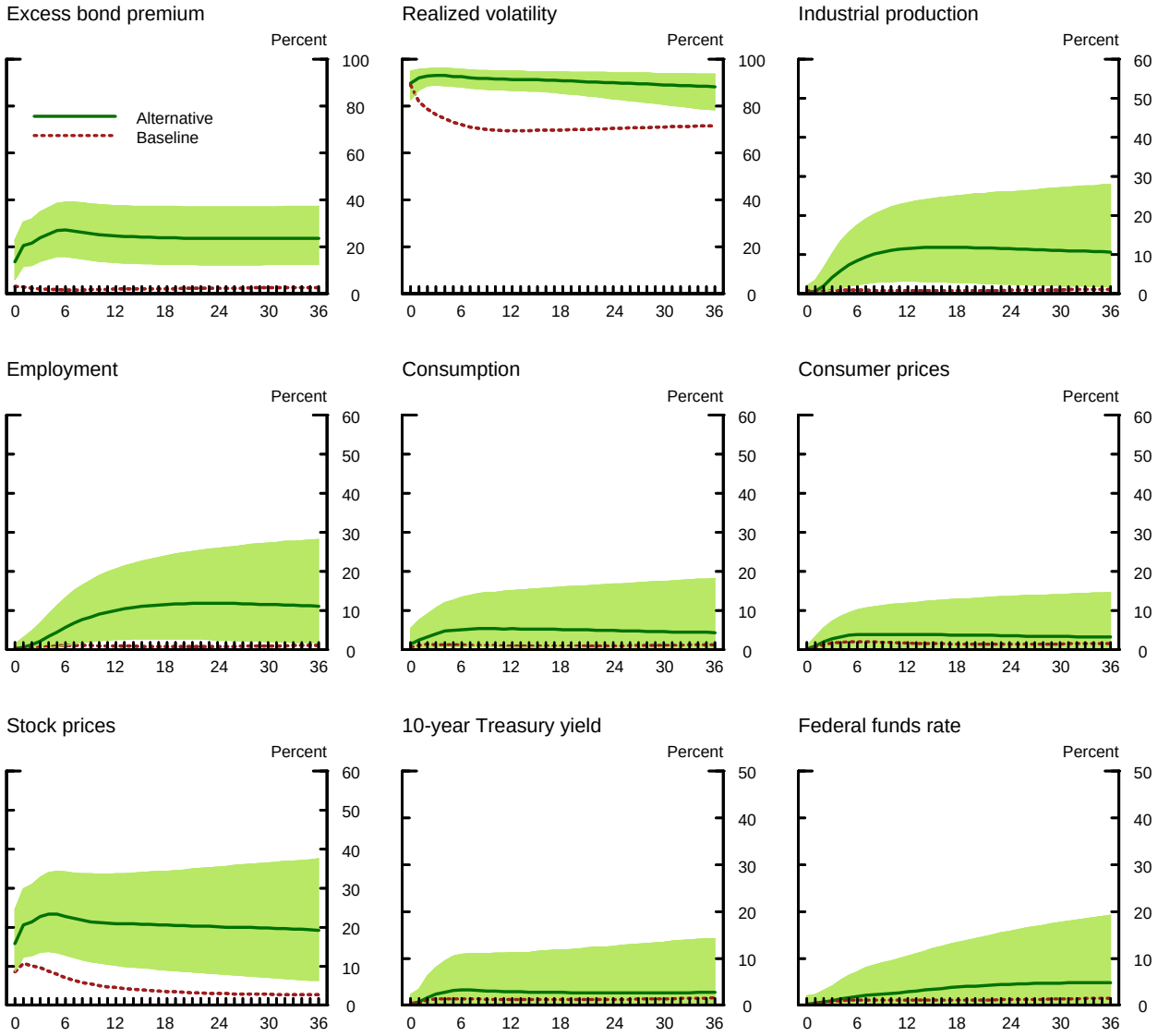
Figure 7: Macroeconomic Impact of an Uncertainty Shock
(Baseline Identification Scheme)



NOTE: The solid line in each panel depicts the median impulse response of the specified variable to a 1 standard deviation shock to the RVOL uncertainty measure identified using the baseline identification scheme (see the text for details). Shaded bands denote the 90-percent pointwise credible sets.

important conduit through which fluctuations in uncertainty are propagated to the real economy (see Arellano et al., 2012; Christiano et al., 2014; Gilchrist et al., 2014b). In response to an unanticipated increase in uncertainty, distortions in financial markets induce a tightening of financial conditions—effectively reducing the supply of credit available to businesses and households—which leads to a decline in spending and production and a drop in the stock market. The results also indicate that financial disturbances have a large effect on economic activity that is largely independent of the level of uncertainty in the economy. And lastly, the above evidence supports the

Figure 8: Forecast Error Variance Decomposition of an Uncertainty Shock
(Baseline vs. Alternative Identification Scheme)



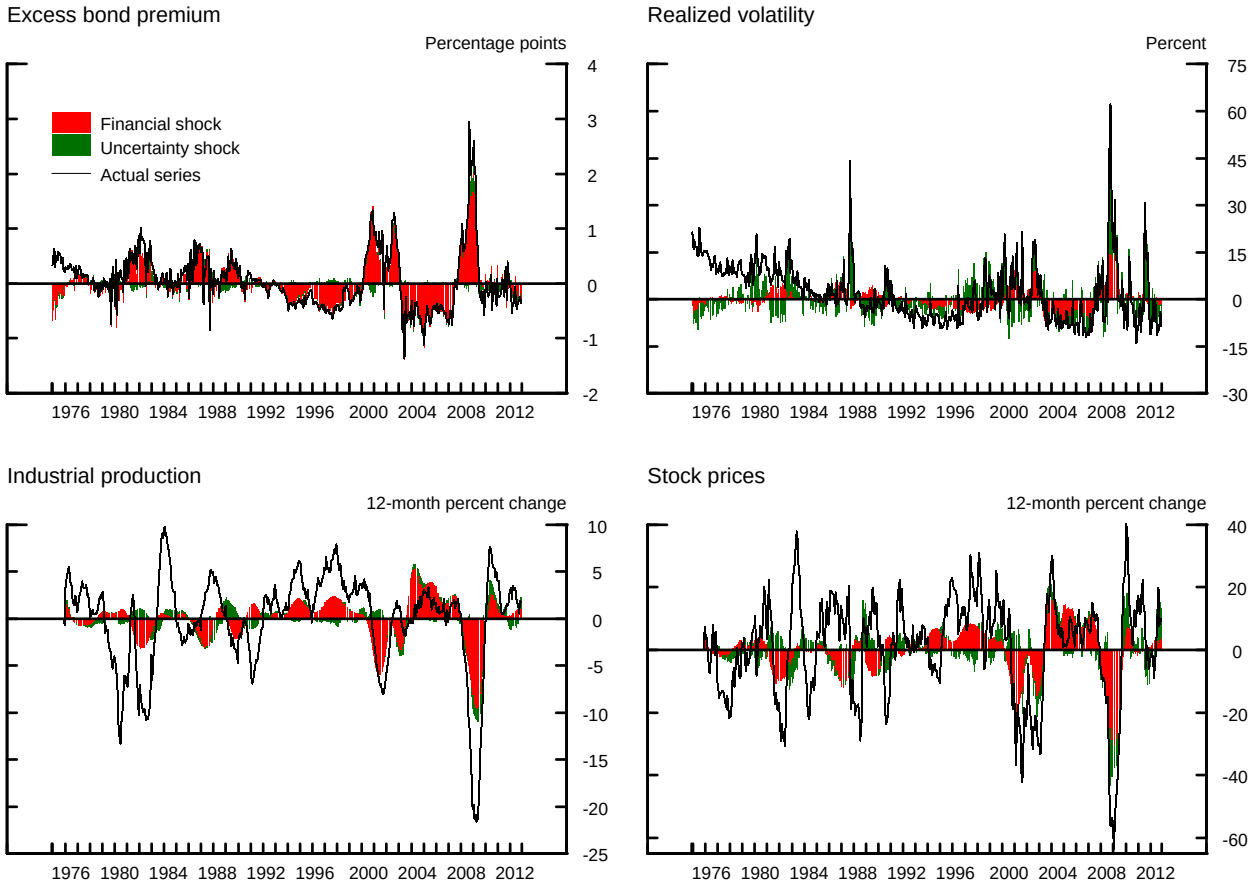
NOTE: The solid (dotted) line in each panel depicts the median estimate of the portion of the forecast error variance of a specified variable attributable to a 1 standard deviation shock to the RVOL uncertainty measure under the baseline (alternative) identification scheme (see the text for details). Shaded bands denote the 90-percent pointwise credible sets corresponding to the alternative identification scheme.

view that a significant portion of fluctuations in financial market volatility may be a reflection of changes in the underlying economic and financial conditions (see Bachmann et al., 2013).

5.2 Historical Significance of Financial and Uncertainty Shocks

To put the above results into a historical perspective, this section examines the role of financial and uncertainty shocks in economic fluctuations over roughly the past 40 years. That is, for each

Figure 9: Historical Variance Decomposition
(Baseline Identification Scheme)

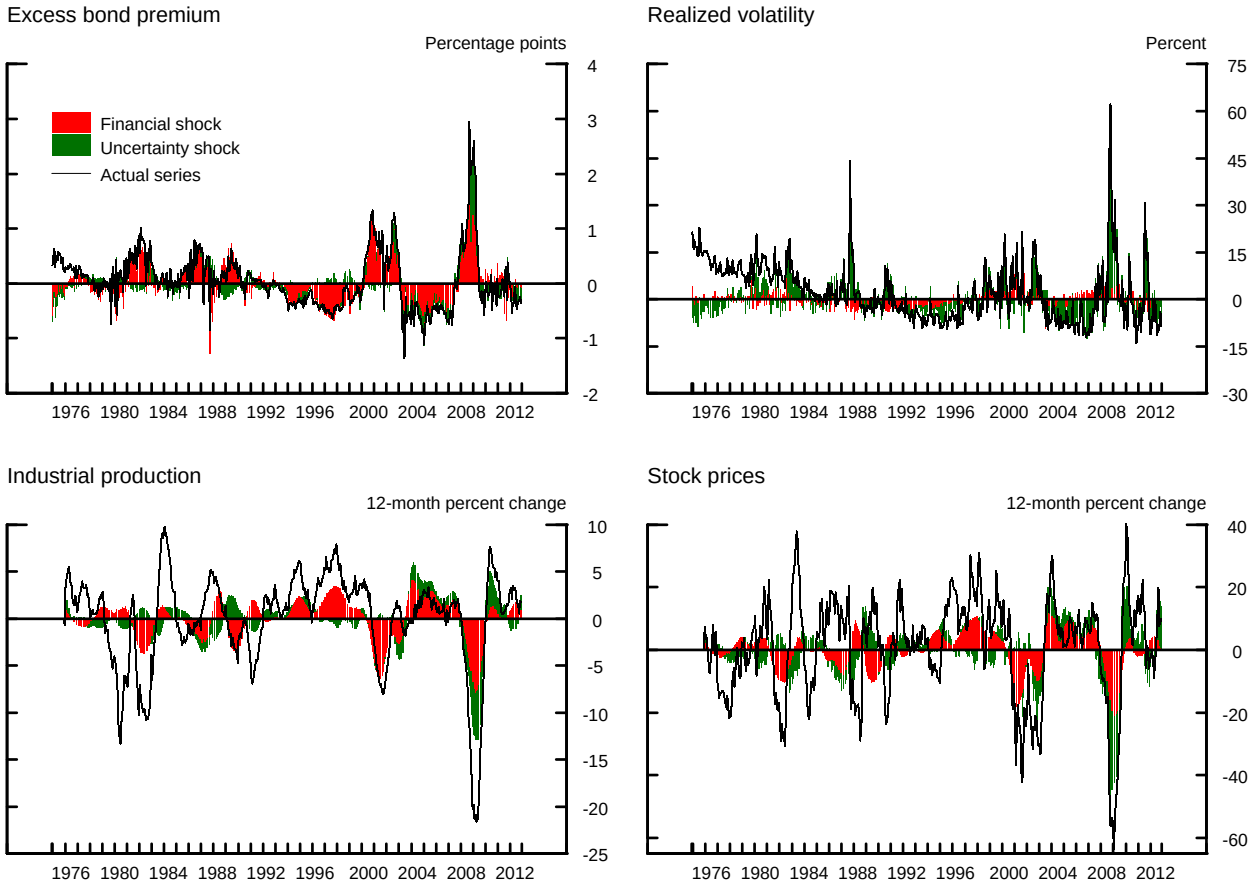


NOTE: The shaded regions in each panel depict the historical contributions of shocks to the EBP (red) and the RVOL uncertainty measure (green) to the specified variable; the two shocks are estimated using the baseline identification scheme. The actual series (solid lines) are expressed in deviations from their respective estimated means (see the text for details).

variable, we calculate the portion of the actual series that is attributable to the two types of shocks over the 1975–2012 period. The results of this exercise for the baseline identification scheme are shown in Figure 9, while those based on the alternative identification are shown in Figure 10. To conserve space, we report the historical variance decomposition only for the EBP, the RVOL measure of uncertainty, the growth in industrial production, and the stock market return. (The results for the remaining endogenous variables are collected in Appendix B.)

According to the historical decomposition implied by the baseline identification scheme, the ups and downs in economic activity over the past two decades were shaped importantly by shocks emanating from the financial sector. Importantly, these shocks account for virtually all of the movements in the EBP, a strong indication that this financial indicator accurately captures disruptions in the credit-intermediation process. Uncertainty shocks implied by the baseline identification scheme, by contrast, do not appear as a significant source of business cycle fluctuations. Moreover,

Figure 10: Historical Variance Decomposition
(Alternative Identification Scheme)



NOTE: The shaded regions in each panel depict the historical contributions of shocks to the EBP (red) and the RVOL uncertainty measure (green) to the specified variable; the two shocks are estimated using the alternative identification scheme. The actual series (solid lines) are expressed in deviations from their respective estimated means (see the text for details).

the identified financial shocks account, on balance, for about as much of the variability in the RVOL measure of uncertainty as do the uncertainty shocks, a result consistent with the notion that heightened economic uncertainty is in large part an outcome of financial instability.

Nevertheless, the economic significance of financial shocks has varied considerably over the past four decades. Such shocks played a distinctly secondary role in economic fluctuations during the first half of our sample, a finding consistent with the heavy regulation of financial institutions and markets during this period and the empirical evidence showing that the economic downturns of the 1970s were influenced significantly by the OPEC-induced increases in oil prices (see Hamilton, 1983, 2003), while the recessions of the early 1980s owed importantly to the tightening of monetary policy under the then-Fed Chairman Volcker, who was determined to fight inflation and reverse the rise in inflation expectations (see Lindsey et al., 2005).

Financial shocks, however, assumed new importance in the wake of financial deregulation and

the associated financial deepening that took place during the second half of the 1980s and the early 1990s. According to our estimates, a pronounced tightening in credit market conditions occurred during periods surrounding the 2001 and 2007–09 cyclical downturns, and adverse credit supply shocks account for significant portions of the decline in industrial output and equity valuations during these two recessions. On the other hand, easy financial conditions—at least in retrospect—characterized much of the mid-1990s and mid-2000s, and economic activity and the stock market were buoyed substantially by expansionary credit supply shocks.

As shown in Figure 10, a qualitatively similar historical narrative emerges under the alternative identification of the two types of shocks. As before, historical changes in credit market conditions are driven primarily by financial shocks, although adverse uncertainty shocks contributed notably to the massive and widespread tightening in financial conditions experienced at the nadir of the 2008–09 financial crisis. And while financial disturbances become a less important source of fluctuations in economic uncertainty under the alternative identification scheme, these shocks remain a significant source of macroeconomic instability during the second half of our sample period. A meaningful economic significance of uncertainty shocks, by contrast, appears to be confined to the "Great Recession" and its immediate aftermath. In general, uncertainty shocks have contributed systematically to swings in equity prices over the past 40 years or so, but their impact on the real economy—insofar they have induced a change in broad financial conditions—appears to have been quite limited.

5.3 Validation of Financial and Uncertainty Shocks

The historical variance decomposition presented above clearly indicates that the identified financial shocks—and to a lesser extent uncertainty shocks—were an important driver of fluctuations in economic activity and swings in broad equity prices since the mid-1980s. At the same time however, a natural question that emerges from this analysis is whether these two types of shocks in fact represent distinct sources of cyclical fluctuations or whether they are simply emblematic of traditional origins of macroeconomic instability.

To examine this hypothesis more formally, we look at the correlations between the identified financial and uncertainty shocks and other widely cited economic disturbances, all of which are external to our VAR system. At monthly frequency, we consider two types of popular shocks: monetary policy and oil price shocks. To measure unanticipated changes in the stance of monetary policy, we rely on high-frequency financial market data. Our first monetary policy shock corresponds to the "target surprise" proposed by Kuttner (2001), which measures the unexpected change in the target federal funds rate associated with an FOMC announcement.[16] In addition, we use changes in the (on-the-run) 2-year Treasury yield over a narrow window bracketing FOMC announcements

[16]Specifically, the unanticipated change in the funds rate is calculated as the change—with minor adjustments—in the current-month federal funds futures contract rate in a 30-minute window (10 minutes before to 20 minutes after) around the FOMC announcement; see Kuttner (2001) for details. These target surprises, as they are commonly referred to in the literature, have been used extensively to examine the effects of monetary policy on asset prices (see Gürkaynak et al., 2005; Bernanke and Kuttner, 2005).

as monetary policy surprises, which provide a more complete characterization of the unanticipated changes in the stance of policy, according to Gilchrist et al. (2014a).[17]

We also consider two monthly measures of oil price shocks. The first measure is the widely used nonlinear transformation of the nominal price of crude oil—the so-called net oil price increase—proposed by Hamilton (2003). The second measure corresponds to the oil supply shock due to Killian (2009), who employs a SVAR-based approach to identify the underlying demand and supply shocks in the global crude oil market.

At quarterly frequency, we concern ourselves with technology and fiscal shocks. The first set of technology shocks corresponds to shocks to labor productivity identified by Mertens and Ravn (2011a) using a SVAR-based approach, which are orthogonal to tax shocks derived from the narrative approach of Romer and Romer (2010). As an alternative proxy, we also use a simple quarterly growth rate in the utilization-adjusted total factor productivity (TFP), which attempts to adjust measured TFP for a range of non-technological factors that can drive a wedge between TFP and technology (see Basu et al., 2006).

On the fiscal front, we consider the surprise tax policy changes from Mertens and Ravn (2011b), which are based on the narrative approach of Romer and Romer (2010); the anticipated tax policy changes of Leeper et al. (2013); and the unanticipated changes in the expected present value of government spending in response to military events from Owyang et al. (2013). All told, our list of external shocks spans the space of disturbances commonly considered to be the most important drivers of aggregate fluctuations.

The pairwise correlations between these external shocks and our identified financial and uncertainty shocks are reported in Table 4. As evidenced by the entries in the table, there appears to be no systematic contemporaneous association between financial and uncertainty shocks and other typical macroeconomic disturbances under either identification scheme. Virtually all pairwise correlations are statistically indistinguishable from zero and all of them are very small in economic terms. These results provide strong corroborative evidence for our view that the identified financial and uncertainty shocks represent independent sources of economic disturbances, with the former category playing an especially salient role in business cycle fluctuations over the past two decades.

Additional corroborative evidence for this view can also be gleaned from within our framework. A distinct feature of financial shocks emphasized in the literature is their effect on credit flows. In particular, an adverse financial shock should, by limiting the availability of credit, lead to a decline in bank lending to businesses and households—in fact, this aspect of financial shocks is used frequently to identify credit supply shocks using sign restrictions. To see whether the identified financial shocks are consistent with this intuitive feature, we augment our benchmark

[17] As emphasized by Gürkaynak et al. (2005), using solely the target surprises to characterize the unanticipated changes in the stance of monetary policy is incomplete because such an approach omits the effect of changes in the future policy rates that are independent of the shock to the current target rate and which are closely associated with the FOMC statements that accompany changes in the target rate. As shown by Gilchrist et al. (2014a), however, the first-order effects of monetary policy actions can be summarized adequately by the intraday changes in the 2-year nominal Treasury yield bracketing FOMC announcements; see also Hanson and Stein (2012) and Gertler and Karadi (2013).

Table 4: Correlations Between Financial, Uncertainty and Other External Shocks

	Identification Scheme			
	Baseline		Alternative	
	Financial	Uncertainty	Financial	Uncertainty
A. Monthly External Shocks				
FFR target surprises[a]	0.04	−0.07	0.05	0.03
2-year Treasury yield surprises[b]	0.04	−0.10	0.05	−0.08
Net oil price increases[c]	−0.01	0.01	0.02	0.01
Oil supply shocks[d]	0.10*	−0.03	0.07	−0.00
B. Quarterly External Shocks				
Technology shocks[e]	−0.09	0.08	−0.08	0.00
TFP shocks[f]	−0.06	0.04	−0.11	0.10
Unanticipated tax shocks[g]	−0.06	−0.05	−0.01	−0.09
Anticipated tax shocks[h]	0.08	0.06	0.04	0.01
Defense spending shocks[i]	0.02	0.06	−0.01	0.07

NOTE: The entries in the table denote the pairwise correlations between the specified external shock and the financial (EBP) and uncertainty (RVOL) shocks identified under the baseline and alternative identification schemes. Monthly financial and uncertainty shocks are estimated over the 1975:M1–2012:M12 period; the quarterly shock series are the quarterly averages of the corresponding monthly values (see the text for details).
* $p < .10$.
[a] Unanticipated changes in the target federal funds rate in the 30-minute window bracketing FOMC announcements; see Kuttner (2001) (1992:M2–2012:M12, $T = 251$).
[b] Changes in the (on-the-run) 2-year Treasury yield in the 30-minute window bracketing FOMC announcements; see Gilchrist et al. (2014a) (1992:M2–2012:M12, $T = 251$).
[c] Net oil price increase; see Hamilton (2003) (1975:M1–2012:M9, $T = 453$).
[d] Crude oil supply shock from Killian (2009) (1975:M1–2007:M12, $T = 396$).
[e] Technology shocks from Mertens and Ravn (2011a) (1975:Q1–2006:Q4, $T = 128$).
[f] Log-difference in the utilization-adjusted TFP; see Basu et al. (2006) (1975:M1–2007:M12, $T = 152$).
[g] Unanticipated tax shocks from Mertens and Ravn (2011b) (1975:Q1–2006:Q4, $T = 128$).
[h] Anticipated tax changes from Leeper et al. (2013) (1975:Q1–2006:Q4, $T = 128$).
[i] Defense spending shocks from Owyang et al. (2013) (1975:Q1–2012:Q4, $T = 152$).

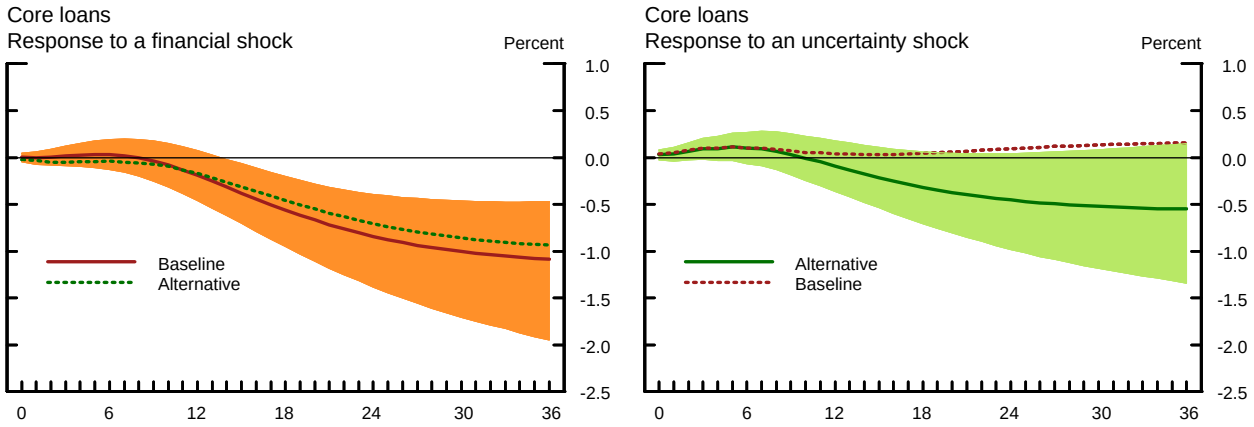
VAR specification with the log of real core loans outstanding.[18] We employ the same two sets of assumptions to jointly identify financial and uncertainty shocks—it is worthwhile to note that this approach imposes no restrictions on the response of bank lending to both shocks. This augmented VAR specification is estimated over the 1986:M1–2012:M12 period reflecting the availability of bank lending data.

Figure 11 traces out the response of bank lending to the two types of shocks.[19] According

[18] Core loans are the sum of loans to households and businesses. Business loans include commercial and industrial (C&I) loans and business loans secured by commercial real estate; household loans include residential mortgages, credit card loans, and other consumer loans. All monthly series were obtained from the Federal Reserve's H.8 Statistical Release. The household and business loans outstanding were deflated by the PCE price deflator.

[19] We do not show responses of other variables in order to conserve space. However, under both identification schemes, the responses of all other variables were qualitatively and quantitatively very similar to those reported in Figures 3, 4, 6, and 7.

Figure 11: Financial and Uncertainty Shocks and Bank Lending
(Baseline vs. Alternative Identification Scheme)



NOTE: The solid (dotted) line in the left panel depicts the median impulse response of real core loans to a 1 standard deviation shock to the EBP identified using the baseline (alternative) identification scheme; shaded bands denote the 90-percent pointwise credible sets corresponding to the baseline identification scheme. The solid (dotted) line in the right panel depicts the median impulse response of real core loans to a 1 standard deviation shock to the RVOL measure of uncertainty identified using the alternative (baseline) identification scheme; shaded bands denote the 90-percent pointwise credible sets corresponding to the alternative identification scheme. Sample period: 1986:M1–2012:M12 (see the text for details).

to the left panel, unanticipated increases in the EBP lead to economically large and statistically significant declines in bank lending under both identification schemes. However, compared with the response of economic activity, the contraction in bank lending occurs with a significant lag. The delayed response of bank lending to an adverse financial shock importantly reflects the fact that firms and households are financing a significant portion of their expenditures by drawing on their existing lines of credit rather than by borrowing through newly issued loans. In the early phases of a financially induced recession, this mechanically boosts the amount of loans on the banks' balance sheets and accounts for the sluggish response of loans outstanding to credit supply shocks (see Bassett et al., 2014a,b).

The response of bank lending to uncertainty shocks (the right panel) is also consistent with our earlier results, which showed that uncertainty shocks had real economic consequences only insofar they led to a change in broad financial conditions. Consistent with this result, positive uncertainty innovations have an economically and statistically significant effect on bank lending effect only under the alternative identification scheme, in which they elicit a concomitant tightening of financial conditions. Under the baseline identification scheme, in contrast, bank lending—like economic activity—shows no response to a jump in the RVOL measure of uncertainty.

6 Robustness Analysis

In this section, we perform several robustness exercises. First, we examine the sensitivity of the results based on the benchmark VAR specification to different sample periods. Second, we analyze the robustness of our results to different measures of uncertainty.

6.1 Alternative Sample Periods

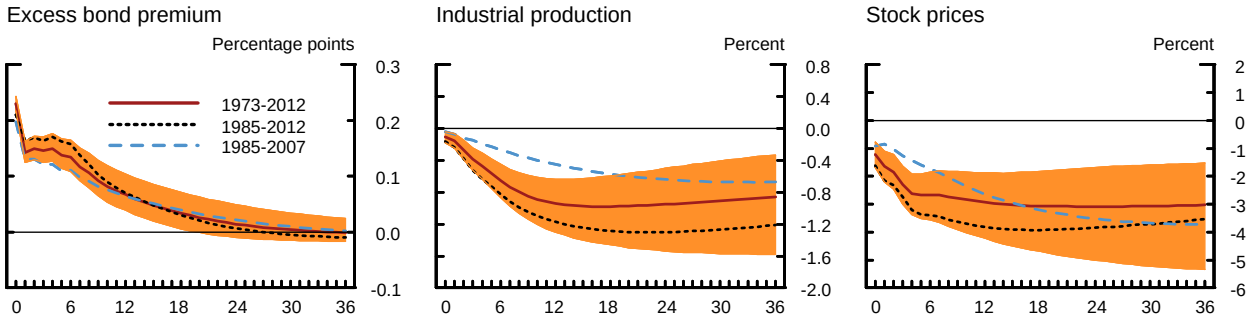
We analyze the robustness of the results reported in Section 5 across two subsamples: (1) the 1985:M1–2012:M12 period; and (2) the 1985:M1–2007:M12 period. The first subsample corresponds to a period characterized by a stable monetary policy regime and by significant deregulation of financial markets. Reflecting the extraordinary events of the 2008–09 financial crisis, the second subsample omits the Great Recession and its aftermath. The results of this exercise are presented in Figure 12. To conserve space, we report only the responses of the EBP, industrial production, and the stock market.[20] For comparison purposes, Figure 12 also includes the benchmark results, which are shown in their original color motifs (see Figures 3, 4, 6, and 7).

The comparison of the solid red and the dotted black lines in Panels (a) and (b) reveals that the effects of financial shocks on economic activity and stock prices during the 1985–2012 period are, if anything, somewhat larger than those based on the full sample period. This result holds across both identification schemes and is consistent with the historical variance decomposition shown in Figures 9 and 10, which showed that financial shocks were an especially significant source of macroeconomic instability during that period. As shown by the dashed blue lines, dropping the Great Recession and its aftermath from the 1985–2012 subsample attenuates the near-term response of the macroeconomy to financial shocks. However, the longer-run responses are qualitatively and quantitatively similar to those from the full sample, an indication that our main results are not driven solely by this extraordinary period of financial market turmoil.

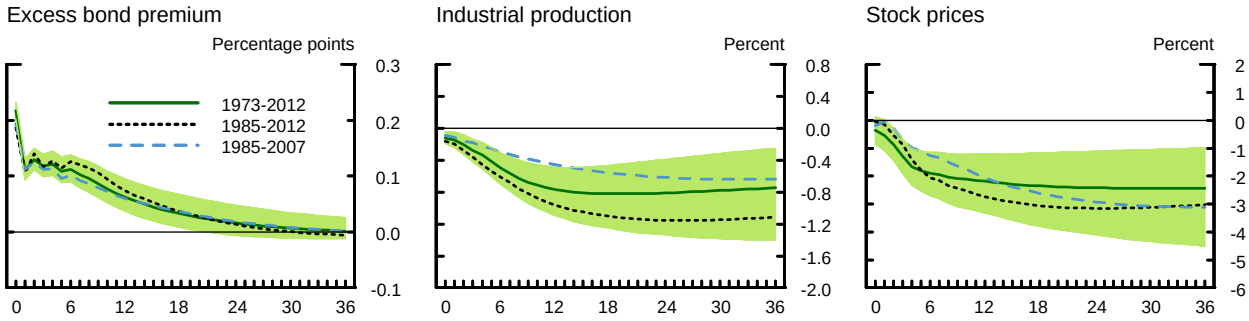
The macroeconomic effects of uncertainty shocks appear to be less robust across the different subsamples. Under the alternative identification scheme (Panel (c)), positive innovations in the RVOL measure of uncertainty during the 1985–2012 period elicit a tightening of financial conditions that is a bit more pronounced compared with that estimated over the full sample. Nevertheless, the response of industrial production is very similar to that from the benchmark specification, while the response of stock prices is somewhat larger over the first 12 months after the shock. Limiting the sample to the 1985–2007 period, by contrast, leads to a more muted EBP response. As a result, the effect of an uncertainty shock on industrial production disappears, highlighting the role that changes in credit market conditions play in propagating financial volatility shocks. Under the baseline identification scheme (Panel (d)), uncertainty shocks have no economically meaningful effect on industrial output in either of the two subsamples, although they continue to affect stock prices at the near-term horizon.

[20] Responses of other variables are available from the authors upon request.

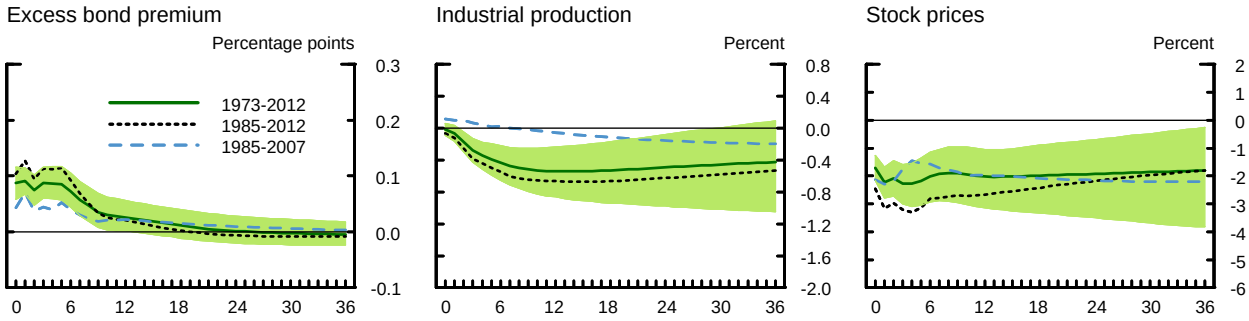
Figure 12: Macroeconomic Implications of Uncertainty and Financial Shocks
(Alternative Sample Periods)



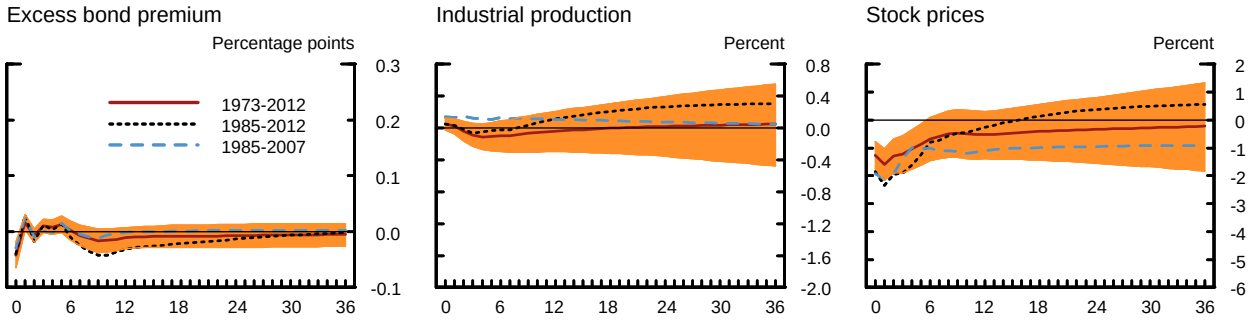
(a) Response of selected variables to the EBP shock – baseline identification scheme



(b) Response of selected variables to the EBP shock – alternative identification scheme



(c) Response of selected variables to the RVOL shock – alternative identification scheme



(d) Response of selected variables to the RVOL shock – baseline identification scheme

NOTE: See the text and notes to Figures 3, 4, 6, and 7 for details.

6.2 Alternative Uncertainty Proxies

Thus far, the macroeconomic effects of uncertainty shocks were based exclusively on the RVOL measure of uncertainty. This section examines the robustness of our results to alternative uncertainty proxies. In performing this analysis, we replace the RVOL uncertainty measure in the VAR specification with a different uncertainty proxy and identify financial and uncertainty shocks using the same two identification schemes as in the benchmark specification. Note that the resulting VAR specifications are estimated over different sample periods, reflecting differences in data availability.

Figure 13 shows the results of this exercise for uncertainty proxies based on equity valuations, while Figure 14 depicts the same information for proxies not based on financial market data. As before, we report only the responses of the EBP, industrial production, and the stock market in order to economize on space.[21]. As shown in Panels (a) and (b) of the two figures, the effects of financial shocks are completely robust with respect to different uncertainty proxies. Under both identification schemes, unanticipated increases in the EBP lead to a pronounced and persistent decline in industrial production and a substantial permanent drop in the stock market. As evidenced by the responses from specifications that includes the VXO and BBD uncertainty indexes, adverse financial shocks are estimated to lead to a considerably more adverse macroeconomic outcomes during the post-1985 period, a result consistent with the subsample analysis reported in Section 6.1.

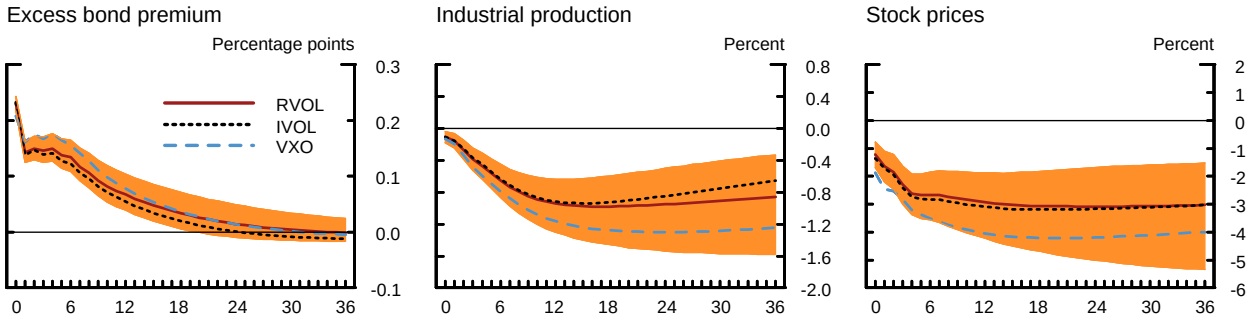
The extent to which uncertainty shocks shape macroeconomic dynamics is less clear, however. Uncertainty proxies based on financial market data (Figure 13) generate fairly similar macroeconomic implications: In all cases, unanticipated jumps in financial market volatility induce a notable tightening of financial conditions under the alternative identification scheme (Panel (c)). It is worth noting that the response of the EBP to an IVOL uncertainty shock is somewhat more muted, reflecting the fact that this measure of idiosyncratic equity volatility is purged of forecastable variation in equity returns and thus is less likely to be contaminated by contractual and informational frictions that plague financial markets. As a result, the effects of IVOL uncertainty shocks on economic activity and stock prices are notably more attenuated compared with those of the RVOL shocks.[22] Predictably, the macroeconomic effects of the IVOL and VXO uncertainty shocks under the baseline identification scheme (Panel (d)) are very similar to those from the benchmark specification: In both cases, increases in financial market volatility have no effect on the EBP or industrial production—they only induce a short-lived decline the stock market.

A similar picture emerges when we consider uncertainty shocks not based on financial market data (Figure 14). As shown in Panels (c) and (d), the BBD and BES uncertainty innovations have meaningful macroeconomic effects only under the alternative identification scheme, in which they induce a change in financial conditions; in fact, the response of both industrial output and the stock market to a BBD uncertainty shock is marginal even in that case, a result consistent with the poor

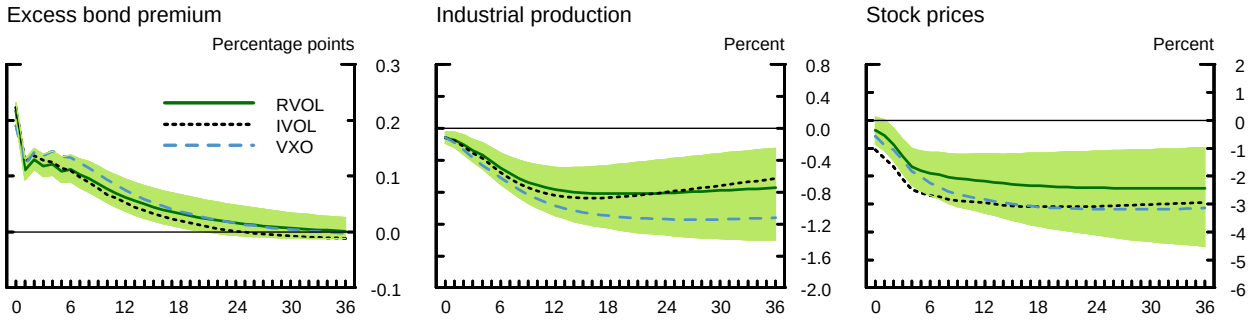
[21] Responses of other variables are again available from the authors upon request. For comparison purposes, both figures also includes the benchmark results, which are again shown in their original color motifs (see Figures 3, 4, 6, and 7)

[22] The differences in the IRFs are not due to different sample period because in this instance, the two VAR specifications are estimated over the same sample period.

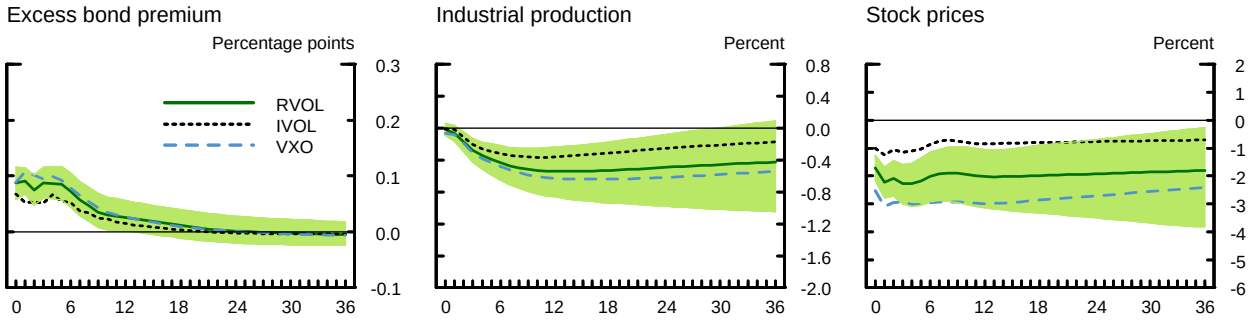
Figure 13: Macroeconomic Implications of Uncertainty and Financial Shocks
(Uncertainty Proxies Based on Financial Market Data)



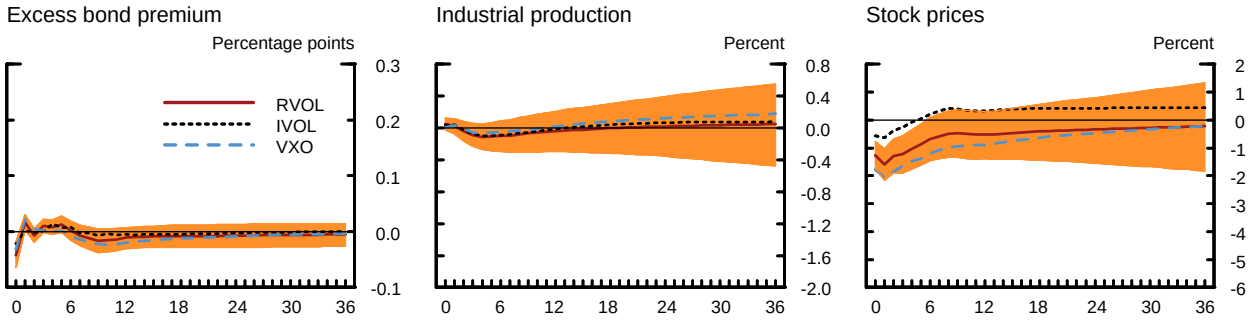
(a) Response of selected variables to a financial shock – baseline identification scheme



(b) Response of selected variables to a financial shock – alternative identification scheme



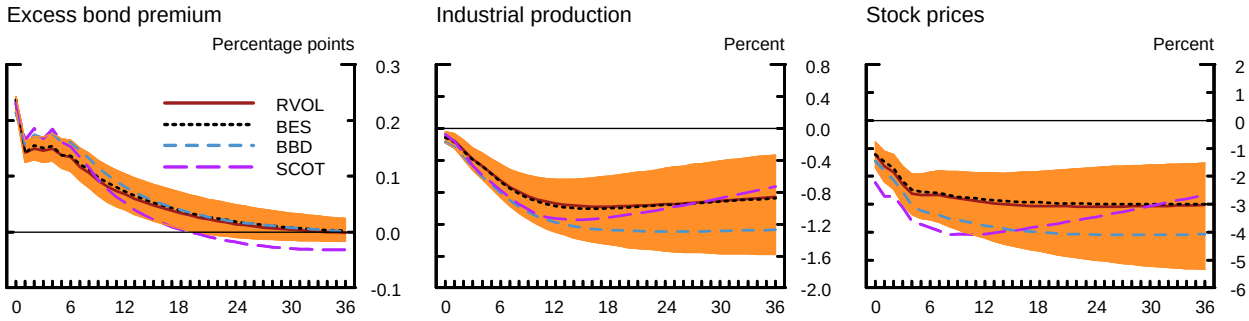
(c) Response of selected variables to an uncertainty shock – alternative identification scheme



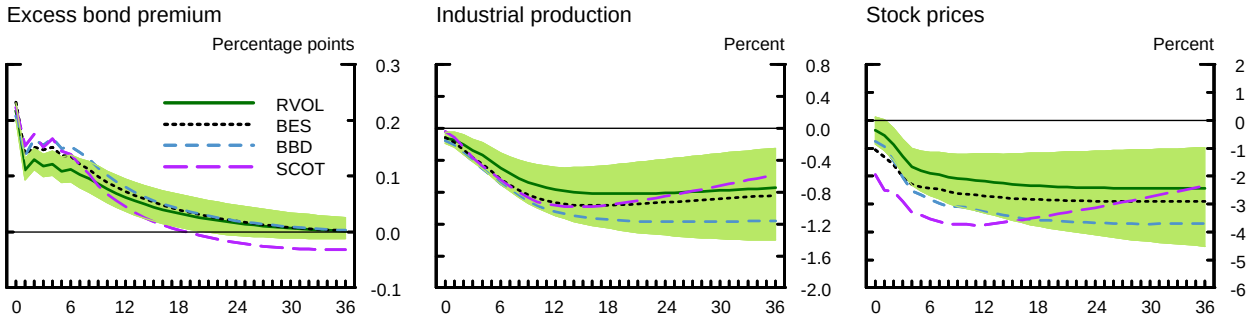
(d) Response of selected variables to an uncertainty shock – baseline identification scheme

NOTE: See the notes to Figures 3, 4, 6, and 7 for details.

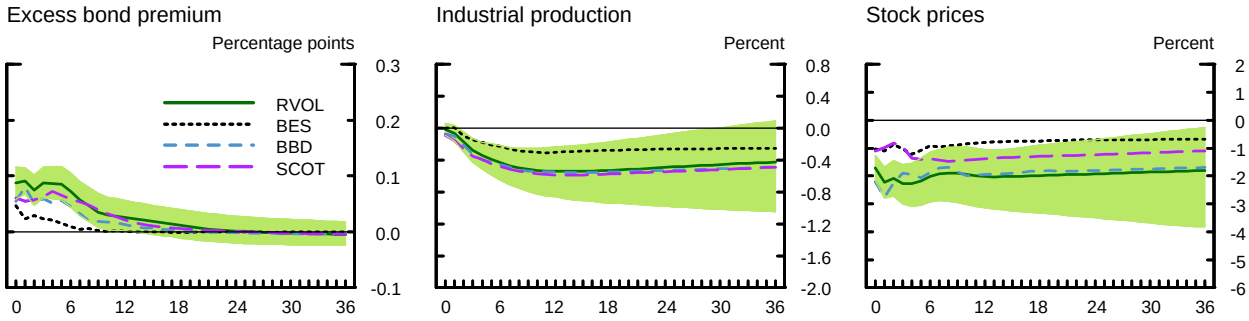
Figure 14: Macroeconomic Implications of Uncertainty and Financial Shocks
(Uncertainty Proxies Not Based on Financial Market Data)



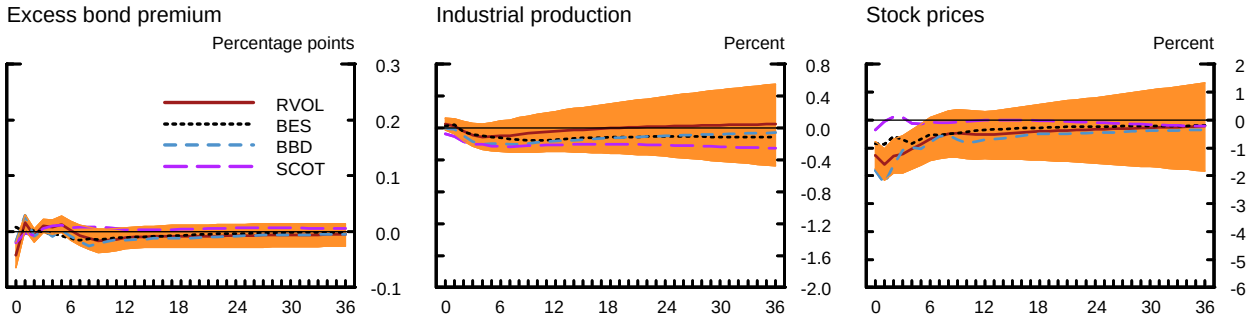
(a) Response of selected variables to a financial shock – baseline identification scheme



(b) Response of selected variables to a financial shock – alternative identification scheme



(c) Response of selected variables to an uncertainty shock – alternative identification scheme



(d) Response of selected variables to an uncertainty shock – baseline identification scheme

NOTE: See the text and notes to Figures 3, 4, 6, and 7 for details.

predictive ability of this uncertainty proxy documented in Section 3.3. By contrast, the impact of financial shocks—under both identification schemes—stays the same, irrespective of the uncertainty measure included in the VAR system.[23]

7 Conclusion

This paper employs the penalty function approach to jointly identify shocks behind changes in financial conditions and economic uncertainty and to trace out the impact of these two types of disturbances on the economy. The two structural innovations are identified using a criterion that each shock should maximize the impulse response of its respective target variable over a pre-specified horizon, an approach that allows us to distinguish between shocks that have otherwise very similar qualitative effects on the economy. Intuitively, we assume that the unanticipated changes in financial conditions are due primarily to financial shocks, whereas fluctuations in economic uncertainty are driven mainly by uncertainty shocks.

We implement this approach in the context of a standard monetary VAR, augmented with the excess bond premium—an indicator of the tightness of financial conditions—and various proxies for macroeconomic uncertainty. The results indicate that financial shocks have a significant effect on the economy: An unanticipated increase in the EBP leads to a modest but persistent rise in uncertainty, a significant decline in economic activity, and a substantial drop in the stock market, dynamics consistent with our maintained assumption that the EBP shocks are capturing disruptions in the credit-intermediation process. Such credit supply shocks also account for a significant portion of the variation in economic activity and broad equity valuations since the mid-1980s.

The results also show that uncertainty shocks have a significant macroeconomic impact in situations where they elicit a meaningful response in the EBP—that is, a tightening of financial conditions; otherwise, the impact of uncertainty shocks on economic activity is substantially attenuated. The fact that uncertainty increases upon impact in response to an adverse financial shock also raises the possibility that fluctuations in uncertainty are influenced importantly by changes in financial conditions, suggesting that heightened economic uncertainty may be a general symptom of financial market disruptions.

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[23]The noticeably more pronounced effect of the EBP shock on stock prices implied by the specification that uses the SCOT uncertainty proxy is a reflection of the 1991:M1–2012:M12 sample period, which is heavily influenced by the Great Recession.

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Appendices

A Uncertainty Measures

This appendix provides a brief description of the six uncertainty proxies used in the analysis.

RVOL measure of uncertainty. Sample period: 1973:M1–2012:M12. The realized equity volatility, our benchmark uncertainty proxy, is calculated as the (annualized) standard deviation of the daily value-weighted total market (log) return from the Center for Research in Security Prices (CRSP) data base. To mitigate the effects of large daily swings in equity prices—many of which occurred during the 2007–08 financial crisis—we use the robust estimator of scale proposed by Rousseeuw and Croux (1993) to calculate the monthly standard deviation of daily stock returns.

IVOL measure of uncertainty. Sample period: 1973:M1–2012:M12. This uncertainty proxy is a monthly version—with minor modifications—of the quarterly measure proposed by Gilchrist et al. (2014b). First, we extracted daily stock returns for all U.S. nonfinancial corporations with at least 500 trading days of data. This selection criterion yielded a panel of 14,706 firms over the period from October 1, 1972 to December 31, 2012. To ensure that our results were not driven by a small number of extreme observations, we eliminated all firm/day observations with a daily absolute return in excess of 50 percent.

The estimate of uncertainty is based on the following three-step procedure. First, we remove the forecastable variation in daily excess returns using the standard (linear) factor model:

$$(R_{it_d} - r^f_{t_d}) = \alpha_i + \boldsymbol{\beta}_i' \mathbf{f}_{t_d} + u_{it_d}, \tag{A-1}$$

where i indexes firms and t_d, $d = 1, \ldots, D_t$, indexes trading days in month t. In equation (A-1), R_{it_d} denotes the (total) daily return of firm i, $r^f_{t_d}$ is the risk-free rate, and $\mathbf{f}_{t_d}$ is a vector of observable risk factors. In implementing the first step, we employ a 4-factor model—namely, the Fama and French (1992) 3-factor model, augmented with the momentum risk factor proposed by Carhart (1997).

In the second step, we use the robust scale estimator of Rousseeuw and Croux (1993) to calculate the monthly firm-specific standard deviation of the daily idiosyncratic returns—that is, the OLS residuals $\hat{u}_{it_d}$ from equation (A-1). Denoted by σ_{it}, this provides us with an estimate of time-varying equity volatility for firm i, a measure that is purged of the forecastable variation in expected returns and thus is less likely to reflect the countercyclical nature of contractual and informational frictions.

In the third step, we assume that the firm-specific measure of uncertainty σ_{it} follows an autoregressive process of the form:

$$\log \sigma_{it} = \gamma_i + \delta_i t + \sum_{k=1}^{3} \rho_k \log \sigma_{i,t-k} + v_t + \epsilon_{it}, \tag{A-2}$$

where γ_i denotes a firm fixed effect intended to control for the cross-sectional heterogeneity in σ_{it}, while the firm-specific term $\delta_i t$ captures secular trends in the idiosyncratic risk of publicly traded U.S. nonfinancial firms documented by Campbell et al. (2001).

The IVOL uncertainty proxy corresponds to the sequence of estimated time fixed effects $\hat{v}_t$, $t = 1, \ldots, T$, which captures shocks to idiosyncratic volatility that are common to all firms. As emphasized by Gilchrist et al. (2014b), the presence of the common variation in the volatility of idiosyncratic equity returns is essential because if fluctuations in idiosyncratic volatility were themselves entirely idiosyncratic, the macroeconomic impact of such uncertainty shocks should wash out in the aggregate.

VXO measure of uncertainty. Sample period: 1986:M1–2012:M12. The VXO uncertainty proxy corresponds to the option-implied volatility calculated from a hypothetical at the money S&P 100 option 30 days to expiration.

BBD measure of uncertainty. Sample period: 1985:M1–2012:M12. This index of policy-related economic uncertainty is an amalgam of three components: (1) the frequency of newspaper references to policy-related economic uncertainty; (2) the number and revenue impact of federal tax code provisions set to expire in future years; and (3) the disagreement among professional forecasters on future government purchases and future inflation.

BES measure of uncertainty. Sample period: 1973:M1–2011:M12. To measure economic uncertainty, Bachmann et al. (2013) construct a measure of forecast dispersion 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 their expectations of future business conditions. Bachmann et al. (2013) focus on two questions:

1. *General Business Conditions*: What is your evaluation of the level of general business activity six months from now versus [current month]? *Answers*: decrease; no change; increase.

2. *Company Business Indicators*: Shipments six months from now versus [current month]? *Answers*: decrease; no change; increase.

The qualitative survey responses to both questions are coded into three discrete numerical categories: -1 = decrease; 0 = no change; and 1 = increase.

For each question, Bachmann et al. (2013) define Frac_t^+ as the (unweighted) proportion of firms that responded with "increase" at time t and Frac_t^- as the (unweighted) proportion of firms that responded with "decrease" at time t. The cross-sectional forecast dispersion for any of the two questions is then computed according to

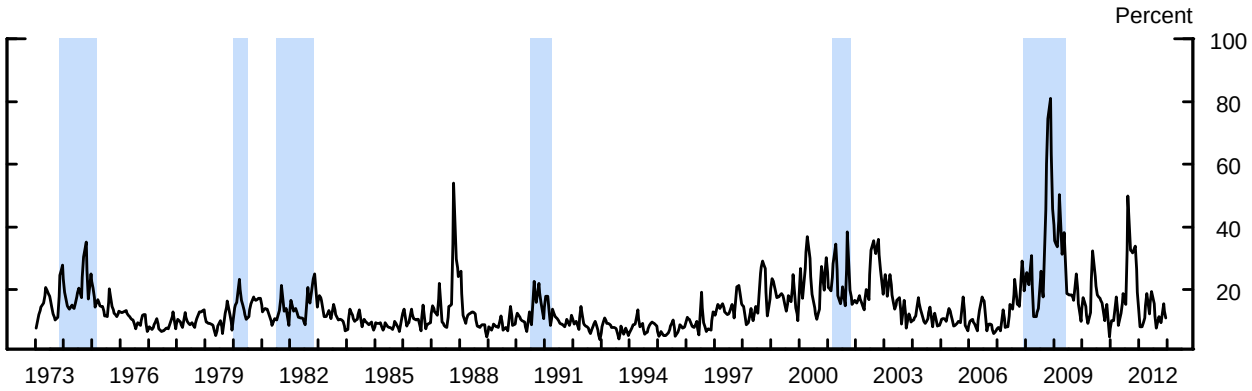
$$D_t = \sqrt{\text{Frac}_t^+ + \text{Frac}_t^- - \left(\text{Frac}_t^+ - \text{Frac}_t^-\right)^2}.$$

The measure of time-varying business-level uncertainty used in this paper corresponds to the cross-sectional forecast dispersion for the question pertaining to general business conditions.

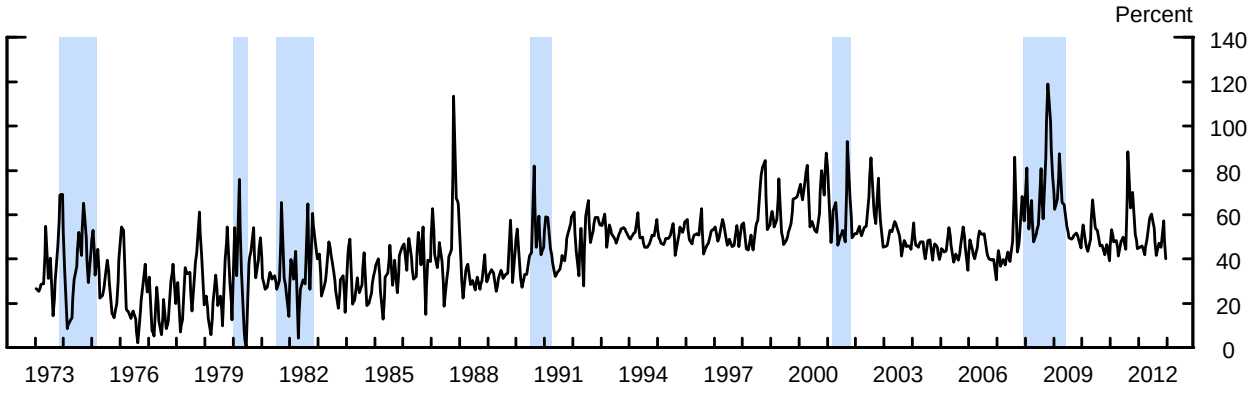
SCOT measure of uncertainty. Sample period: 1991:M1–2012:M12. This real-time uncertainty index measures the degree of uncertainty about real economic activity among financial market participants. Specifically, Scotti (2013) first estimates a dynamic factor model on actual economic data releases to construct monthly business conditions indexes and compute the associated forecasting weights. An economic data "surprise" corresponds to the difference between the actual data release and its median expectation from Bloomberg. The uncertainty index is computed as the square root of the weighted average of the squared surprises, where the time-varying weights are the forecasting weights from the estimation of the dynamic factor model in the first stage.

Figure A-1 shows the the time paths of the three uncertainty proxies that rely on financial market data (RVOL, IVOL, and VXO), while Figure A-1 shows the time-series evolution of uncertainty measures not based on financial market data (BBD, BES, and SCOT).

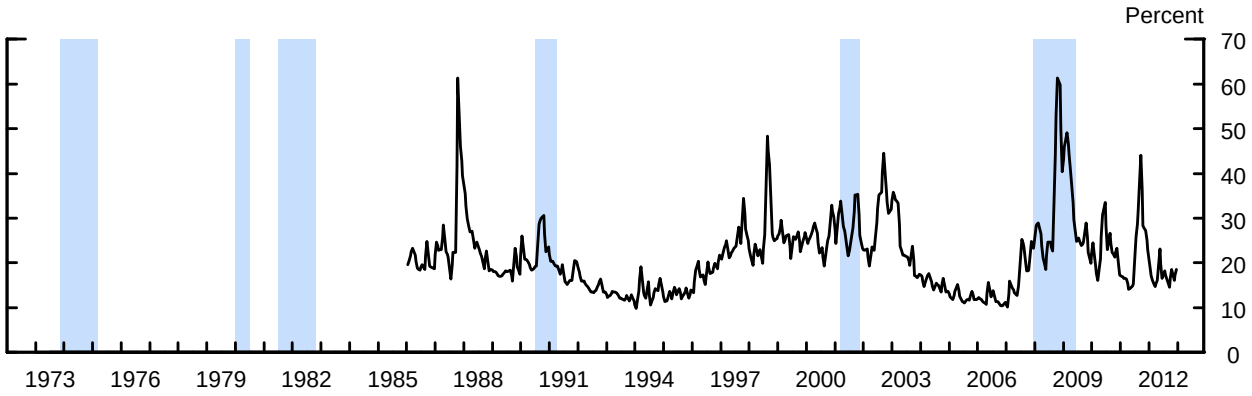
Figure A-1: Uncertainty Measures
(Proxies Based on Financial Market Data)



(a) Realized stock market volatility (RVOL)



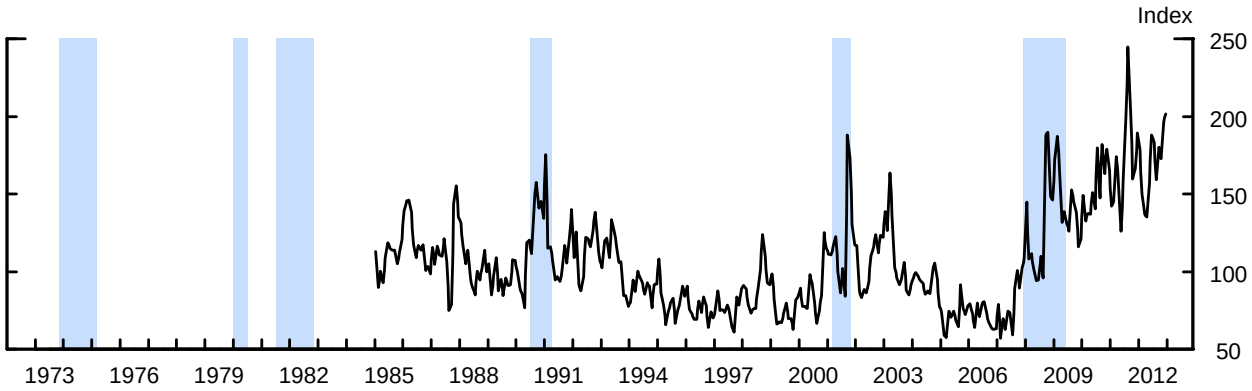
(b) Idiosyncratic stock market volatility (IVOL)



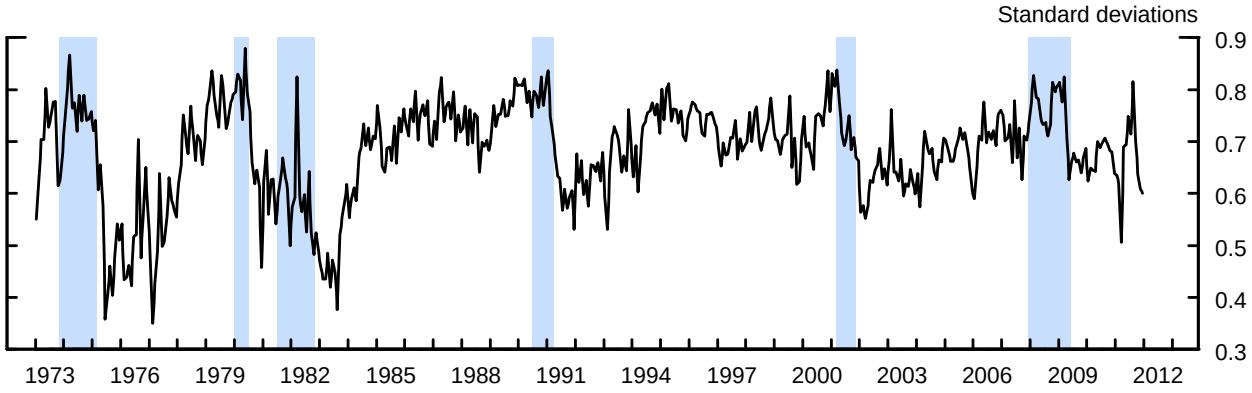
(c) Option-implied volatility on the S&P 100 stock futures index (VXO)

NOTE: The panels of the figure show the three different measures of economic uncertainty based on equity valuations (see the text for details). The shaded vertical bars denote the NBER-dated recessions.

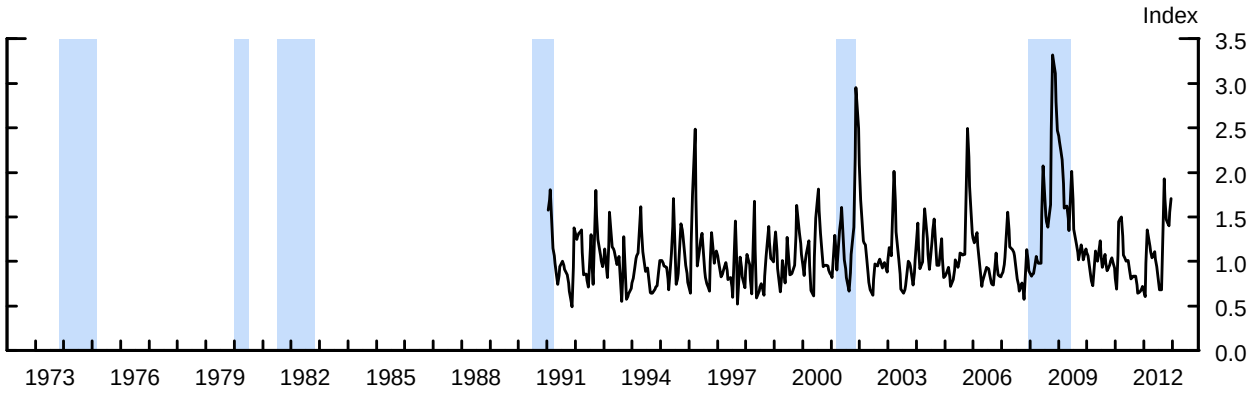
Figure A-2: Uncertainty Measures
(Proxies Not Based on Financial Market Data)



(a) Economic policy uncertainty index (BBD)



(b) Uncertainty based on forecast dispersion (BES)

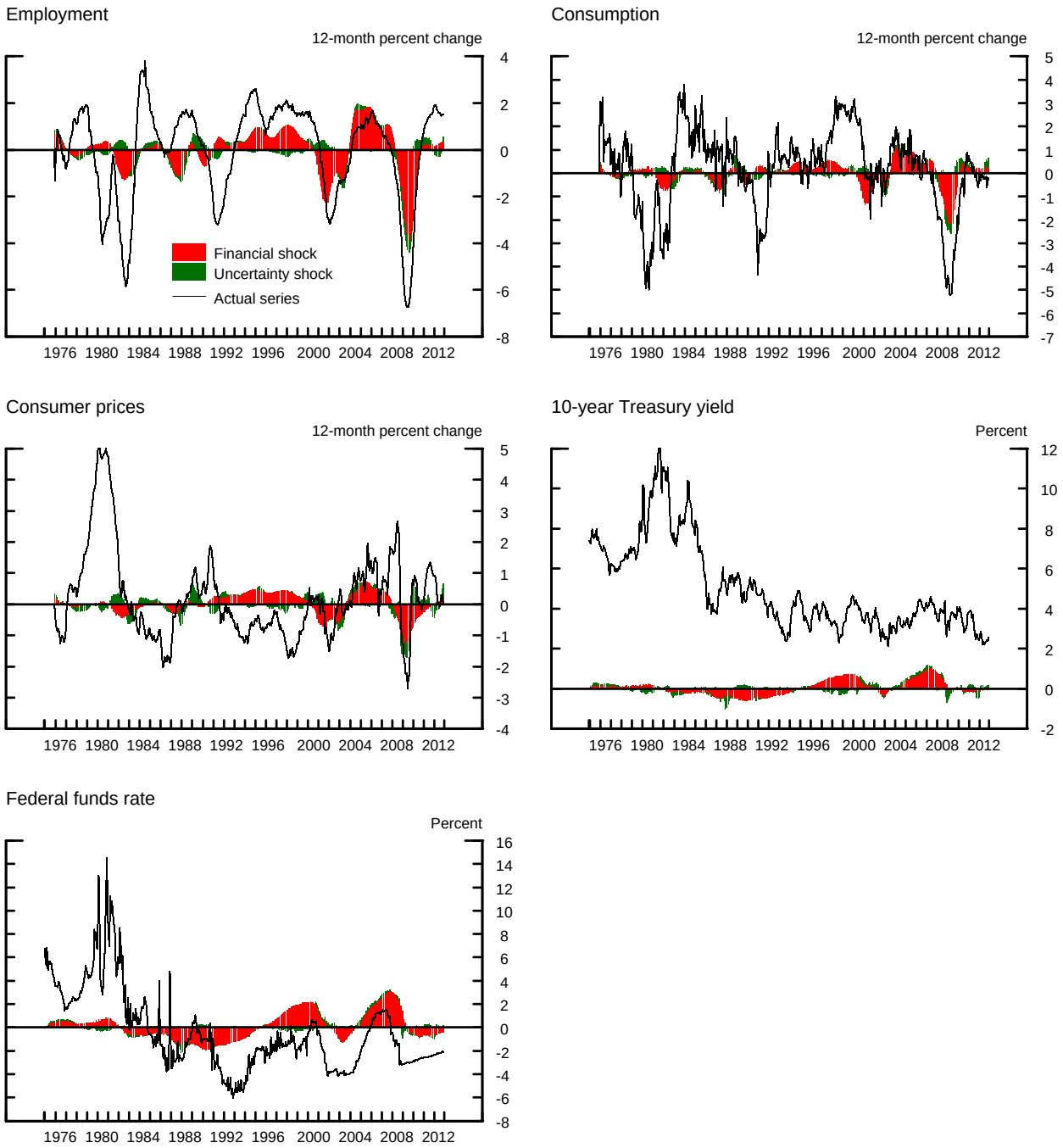


(c) Uncertainty index based on economic data surprises (SCOT)

NOTE: The panels of the figure show the three different measures of economic uncertainty that are not based on equity valuations (see the text for details). The shaded vertical bars denote the NBER-dated recessions.

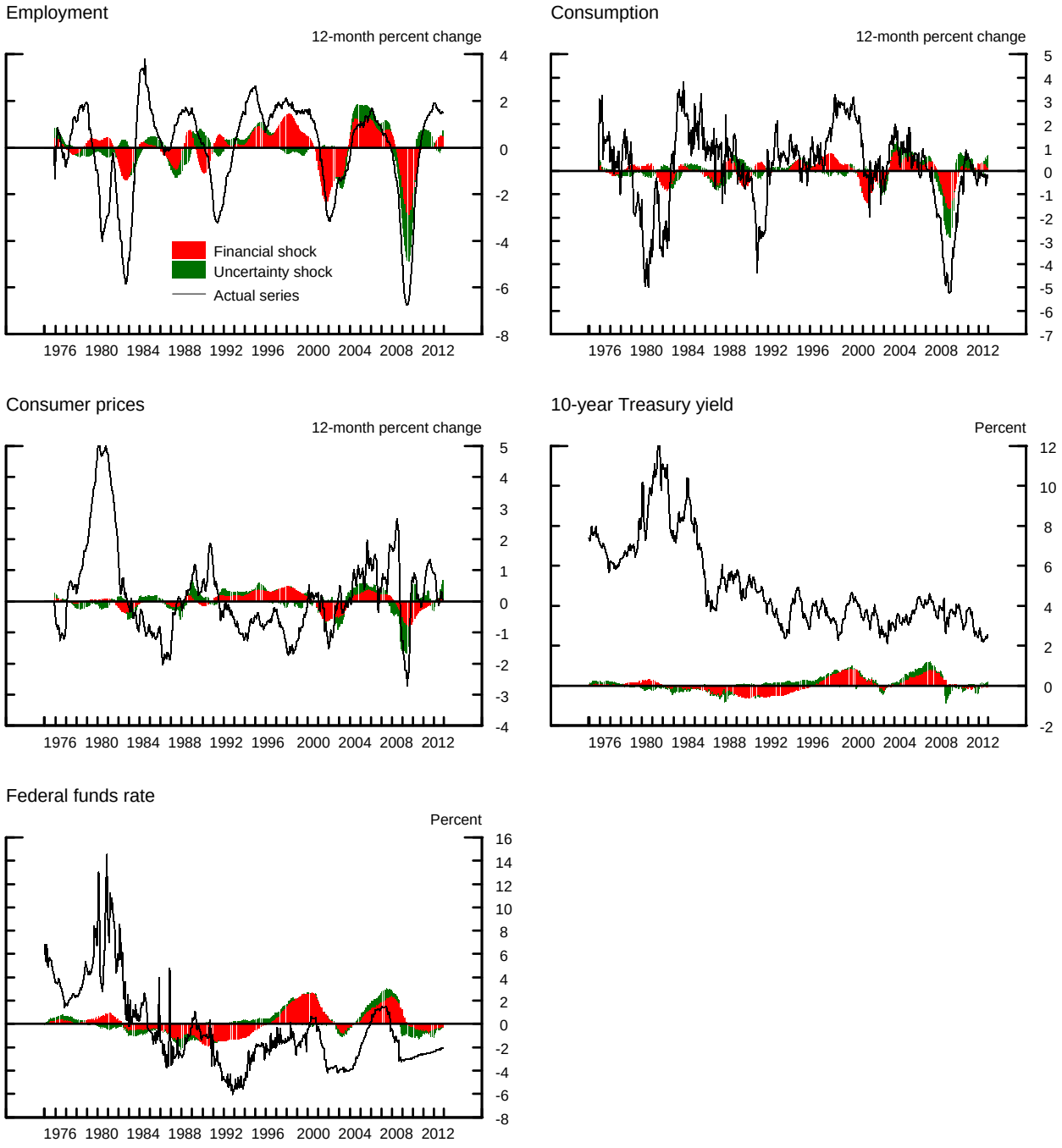
B Historical Variance Decomposition

Figure B-1: Historical Variance Decomposition
(Baseline Identification Scheme)



NOTE: The panels of the figure depict the historical contributions of shocks to the EBP (red) and the RVOL uncertainty measure (green) to the specified variable; the two shocks are estimated using the baseline identification scheme. See the main text and notes to Figure 9 for details.

Figure B-2: Historical Variance Decomposition
(Alternative Identification Scheme)



NOTE: The panels of the figure depict the historical contributions of shocks to the EBP (red) and the RVOL uncertainty measure (green) to the specified variable; the two shocks are estimated using the alternative identification scheme. See the main text and notes to Figure 10 for details.