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UNCERTAINTY SHOCKS AND UNEMPLOYMENT DYNAMICS: AN ANALYSIS OF POST-WWII U.S. RECESSIONS

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Uncertainty Shocks and Unemployment Dynamics: An Analysis of Post-WWII U.S. Recessions*

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Abstract

We investigate the effects of uncertainty shocks on unemployment dynamics in the post-WWII U.S. recessions via non-linear (Smooth-Transition) VARs. The relevance of uncertainty shocks is found to be much larger than that predicted by standard linear VARs in terms of i) magnitude of the reaction of the unemployment rate to such shocks, ii) welfare costs computed by considering conditional macroeconomic volatilities, iii) contribution to the variance of the prediction errors of unemployment at business cycle frequencies. We discuss the ability of different classes of DSGE models to replicate our results. Our findings reinforce the relevance of the trade-off between "correctness" and "timeliness" of policy-makers' decisions.

Keywords: Uncertainty shocks, Unemployment Dynamics, Smooth Transition Vector-AutoRegressions, Recessions.

JEL codes: C32, E32, E52.

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1 Introduction

> *"There's pretty strong evidence that the rise in uncertainty is a significant factor holding back the pace of recovery now. [...] research shows that heightened uncertainty slows economic growth, raises unemployment, and reduces inflationary pressures. [...] There's no question that slow growth, high unemployment, and significant uncertainty are challenges for monetary policy."* John Williams, President and Chief Executive Officer of the Federal Reserve Bank of San Francisco, FRBSF Economic Letter, January 21, 2013.

The U.S. unemployment rate has experienced a substantial upswing during the 2007-2009 economic crisis, moving from 4.4% in May 2007 to 10.1% in October 2009. Since then, the recovery of the labor market has been marked but not full. In January 2013, unemployment was assessed to be some 2% larger than its longer-run value by most FOMC participants (Yellen, 2013). Clearly, the identification of the drivers behind the evolution of the U.S. unemployment rate is of primary importance to policymakers.[1]

This paper investigates the impact of uncertainty shocks on unemployment during U.S. post-WWII recessionary episodes. Since the seminal contribution by Bloom (2009), a large number of papers have been concerned with the role of uncertainty at a macroeconomic level.[2] Part of the literature has studied the impact of uncertainty shocks with Dynamic Stochastic General Equilibrium models.[3] A related empirical literature has dealt with the identification of uncertainty shocks by employing *linear* VAR models. Recent contributions include Bloom (2009), Alexopoulos and Cohen (2009), Bachmann, Elstner, and Sims (2013), Mumtaz and Theodoridis (2012), Baker, Bloom, and Davis (2013), Gilchrist, Sim, and Zakrajsek (2013), Leduc and Liu (2013), Colombo

[1] According to the Federal Reserve Act, the promotion of maximum sustainable output and employment is one of the two ultimate goals of the Federal Reserve, the other one being the promotion of stable prices. In December 2012, the FOMC decided *"[...] to keep the target range for the federal funds rate at 0 to 1/4 percent and currently anticipates that this exceptionally low range for the federal funds rate will be appropriate at least as long as the unemployment rate remains above 6-1/2 percent, inflation between one and two years ahead is projected to be no more than a half percentage point above the Committee's 2 percent longer-run goal, and longer-term inflation expectations continue to be well anchored."* See http://www.federalreserve.gov/newsevents/press/monetary/20121212a.htm .

[2] A survey by Bloom, Fernández-Villaverde, and Schneider (2013) discusses the variety of channels through which uncertainty may affect economic agents' decisions.

[3] A non-exhaustive list of studies includes Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe (2011), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012), Benigno, Benigno, and Nisticò (2012), Mumtaz and Theodoridis (2012), Christiano, Motto, and Rostagno (2013), Bianchi and Melosi (2013), Bachmann and Bayer (2013), Bachmann, Elstner, and Sims (2013), and Leduc and Liu (2013).

(2013), and Nodari (2013).[4] Linear VAR frameworks are standard tools in the empirical macroeconomic literature. However, the U.S. unemployment rate has been found to be characterized by asymmetric dynamics across different phases of the business cycle (Koop and Potter, 1999, van Dijk, Teräsvirta, and Franses, 2002, Morley and Piger, 2012, Morley, Piger, and Tien, 2012), a stylized fact which naturally leads to the adoption of non-linear frameworks. Moreover, uncertainty is typically high during recessions, when unemployment also tends to increase abruptly (Jurado, Ludvigson, and Ng, 2013). For these reasons, recessionary episodes are very likely to be quite informative phases for the identification of the effects of uncertainty shocks on unemployment. We elaborate on this point by working with a non-linear framework suited to isolate the impact of uncertainty shocks during recessions.[5] To this aim, we model U.S. quarterly data on uncertainty, unemployment, and other standard macroeconomic variables with Smooth Transition Vector AutoRegression (STVAR) models. The STVAR set up conveniently allows us to isolate recessionary episodes while retaining enough information to estimate a richly parametrized VAR framework. To understand to what extent non-linearities are important for uncovering the effects of uncertainty shocks, we then contrast the predictions of the non-linear STVAR models conditional on recessions with those produced with standard linear VARs.

Our main results are the following. First, we find that the impact of uncertainty shocks on unemployment is substantially underestimated if one does not take into account that they typically occur in recessions. A linear VAR model returns estimates suggesting that a one standard deviation increase in the VIX, our proxy for uncertainty, may induce a reaction of the unemployment rate of about 0.17 percentage points four quarters after the shock, and of about 0.15 percentage points eight quarters after such shock. The non-linear VAR reveals that the same shock, when hitting the economy during a recession, is estimated to induce a much larger (and statistically different) increase in unemployment of 0.38 percentage points four quarters after the shock, and 0.47 two years after the shock. Evidence of non-linear dynamics is also found for the policy rate and inflation. Second, welfare costs computed with an operational loss function of the type used in the empirical literature dealing with labor-market frictions (see, e.g., Sala,

[4] These contributions employ small-scale VARs. However, the importance attributed to uncertainty shocks does not seem to be due to omitted information. Stock and Watson (2012) employ Dynamic Factor models to process a database composed by 200 U.S. economic series. They find uncertainty shocks to be quite relevant for explaining the post-WWII macroeconomic dynamics.

[5] Section 2 develops this argument further. For a paper dealing with instabilities in the macroeconomic effects of uncertainty shocks via a rolling-window VAR approach, see Beetsma and Giuliodori (2012).

Söderström, and Trigari, 2008) are shown to be substantially larger during recessions, by a factor that ranges from 3 to 9. Third, consistently with the previous findings, the contribution of uncertainty shocks to the forecast error variance decomposition of the unemployment rate at business cycle frequencies is estimated to be (at least) three times larger in a non-linear VAR model. Interestingly, such shocks turn out to be more powerful than monetary policy shocks as a driver of the U.S. unemployment rate. A battery of checks, dealing with different sets of variables, identification schemes, and different empirical proxies for uncertainty, confirm the robustness of our results. Wrapping up, the non-linear VAR analysis suggests that uncertainty shocks may be markedly more costly than previously estimated via linear frameworks.[6]

Overall, our findings corroborate those presented in previous contributions on the asymmetries characterizing the evolution of the unemployment rate over the business cycle. Koop and Potter (1999) perform an extensive model comparison involving linear and non-linear models for the U.S. unemployment rate. They find clear evidence in favor of a non-linear threshold autoregressive model featuring two distinct regimes. In their survey on STVAR models, van Dijk, Teräsvirta, and Franses (2002) provide further evidence in favor of asymmetric dynamics of the U.S. unemployment rate across different regimes. Morley and Piger (2012) construct an indicator of the U.S. business cycle by averaging a variety of competing linear and non-linear statistical frameworks. The resulting indicator clearly points to variations in the cycle larger during recessions than in expansionary periods. Interestingly, their measure displays an asymmetric shape and it is shown to be closely related to the unemployment rate. Importantly, Morley, Piger, and Tien (2012) show that the relevance of non-linearities for modeling an indicator of the business cycle survives also when considering a multivariate approach.

Our results are also of interest from a modeling standpoint. Gilchrist and Williams (2005) and Basu and Bundick (2011) show that, in a standard real business cycle (RBC) set up featuring a Walrasian labor market, uncertainty shocks are expansionary because they negatively affect households' wealth, therefore increasing households' marginal utility of consumption and labor supply. Leduc and Liu (2013) show that this conclusion is overturned when some real frictions are added to the framework. In particular, in a

[6] In principle, it is possible that the countercyclical evolution of uncertainty is endogenous and due to movements in the business cycle, more than a cause of such movements. Bachmann and Moscarini (2012) propose a model in which strategic price experimentation during bad economic times (due to first moment shocks) leads to a higher dispersion of firms' profits. Baker and Bloom (2012) use natural disasters and events like terrorist attacks and unexpected political shocks to isolate exogenous increases in uncertainty in a panel of countries. They find the contribution of second moment shocks to explain at least half of the variation in real GDP growth.

model with search frictions in the labor market, positive uncertainty shocks negatively affect potential output. This occurs because firms pause hiring new workers when uncertainty hits the economy due to the lower expected value of a filled vacancy. As a consequence, firms post a lower number of vacancies, so inducing a drop in the job finding rate and an increase in the unemployment rate. In presence of sticky prices in the intermediate sector, this conclusion is reinforced. Facing an uncertainty shock, aggregate demand drops, so leading firms to lower their relative prices. Such decline reduces even further the value of a vacancy, therefore raising unemployment even more. Leduc and Liu (2013) notice that, in a sticky price framework, an uncertainty shock lowers inflation as well, and therefore can be interpreted as a demand shock. Our empirical findings qualify the conclusions of Leduc and Liu (2013), as we show that uncertainty shocks are demand shocks. Hence our results suggest that labor market frictions and sticky prices are relevant frictions to interpret the macroeconomic effects of uncertainty shocks during recessions.

The structure of the paper is the following. Section 2 offers statistical support in favor of a non-linear relationship between unemployment and uncertainty, presents the Smooth Transition VAR model employed in our analysis, and explains the reasons behind our choice of focusing on recessions. Section 3 presents our results, whose robustness is documented in Section 4. Section 5 provides further evidence on the importance to employ non-linear models when dealing with uncertainty shocks. Section 6 concludes.

2 Empirical investigation

The aim of this section is twofold. First, we present our Smooth-Transition VAR model. Second, we discuss the reasons behind our focus on U.S. recessions.

2.1 Data and methodology

As anticipated in the Introduction, we identify the macroeconomic effects of uncertainty shocks during post-WWII U.S. recessions by modeling some selected U.S. macroeconomic series with a Smooth-Transition VAR framework. Granger and Teräsvirta (1993) offer a presentation on STVARs and discusses some issues related to their estimation. A survey on recent developments in this area is proposed by van Dijk, Teräsvirta, and Franses (2002).

Formally, our STVAR model reads as follows:

$$
\begin{aligned}
\boldsymbol{X}_t &= F(z_{t-1})\boldsymbol{\Pi}_R(L)\boldsymbol{X}_t + (1 - F(z_{t-1}))\boldsymbol{\Pi}_{NR}(L)\boldsymbol{X}_t + \boldsymbol{\varepsilon}_t, && (1)\\
\boldsymbol{\varepsilon}_t &\sim N(0, \boldsymbol{\Omega}_t), && (2)\\
\boldsymbol{\Omega}_t &= F(z_{t-1})\boldsymbol{\Omega}_R + (1 - F(z_{t-1}))\boldsymbol{\Omega}_{NR}, && (3)\\
F(z_t) &= \exp(-\gamma z_t)/(1 + \exp(-\gamma z_t)), \gamma > 0, z_t \sim N(0,1). && (4)
\end{aligned}
$$

where $\boldsymbol{X}_t$ is a set of endogenous variables which we aim to model, $F(z_{t-1})$ is a logistic transition function which captures the probability of being in a recession and whose smoothness parameter is γ, z_t is a transition indicator, $\boldsymbol{\Pi}_R$ and $\boldsymbol{\Pi}_{NR}$ are the VAR coefficients capturing the dynamics of the system during recessions and non-recessionary phases (respectively), $\boldsymbol{\varepsilon}_t$ is the vector of reduced-form residuals having zero-mean and whose time-varying, state-contingent variance-covariance matrix is $\boldsymbol{\Omega}_t$, and $\boldsymbol{\Omega}_R$ and $\boldsymbol{\Omega}_{NR}$ are covariance matrices of the reduced-form residuals computed during recessions and non-recessions, respectively.

In short, this model assumes that our endogenous variables can be described as a linear combination of two linear VARs, i.e., one suited to describe the state of the economy during recessions and the other to be interpreted as a "catch all" vector modeling the remaining phase(s). Conditional on the standardized transition variable z_t, the logistic function $F(z_t)$ indicates the probability of being in a recessionary phase.[7] The transition from a regime to another is regulated by the smoothness parameter γ. Large values of this parameter imply abrupt switches from a regime to another. Viceversa, moderate values of γ enable the economic system to spend some time in each regime before switching to the alternative one. Importantly, the STVAR model allows for non-linear effects as for both the contemporaneous relationships and the dynamics of our economic system.

The baseline analysis hinges upon the vector $\boldsymbol{X}_t = [vix_t, \pi_t, u_t, R_t]'$, where vix_t stands for the VIX index, our proxy of uncertainty, π_t stands for inflation, u_t is the unemployment rate, R_t is a policy rate. The Chicago Board Options Exchange Market Volatility Index (the VIX index) measures the implied volatility of the S&P500 index

[7] As suggested by van Dijk, Teräsvirta, and Franses (2002), one may think of this model as a regime-switching framework that allows for two different regimes associated with extreme values of the transition function, i.e., "recessions" when $F(z_t) = 1$, which (under the assumption of $\gamma > 0$) occurs for large negative values of z_t (formally, when $z_t \to -\infty$), and "non-recessions" when $F(z_t) = 0$ (which realizes when $z_t \to \infty$). Alternatively, one may think of a "continuum" of regimes, each associated with a different value of the transition function $F(z_t)$. For simplicity, we will refer in this paper to the two regime-interpretation.

options. This index, often referred to as "fear index", represents a measure of market expectations of stock market volatility at time t over the next 30-day period. Before 1986 this index is unavailable. Following Bloom (2009), we compute pre-1986 monthly returns volatilities by employing the monthly standard deviation of the daily S&P500 index normalized to the same mean and variance as the VIX index from 1986 onward. Inflation is computed as the annualized quarter-on-quarter percentage growth rate of the implicit GDP deflator. Unemployment is the monthly civilian unemployment rate. The policy rate is the federal funds rate. Quarterly observations of monthly data are constructed via quarterly averaging. The sample spans the 1962Q3-2012Q3 period, 1962Q3 being the first available quarter as for the uncertainty index. The source of our data is the FRED database on the Federal Reserve Bank of St. Louis' website.[8]

We employ this dataset to verify the presence of non-linearities in the unemployment-uncertainty relationship. We run two tests. The first one refers to a simple regression modeling unemployment and featuring lags of unemployment, uncertainty, and interaction terms between these two variables as regressors. As shown by Luukkonen, Saikkonen, and Teräsvirta (1988), the assumption of linearity is rejected if the coefficients of the interaction terms are jointly different from zero. To detect non-linear dynamics at a multivariate level, we then perform the test proposed by Teräsvirta and Yang (2013). Their framework is particularly suited for our analysis since it amounts to test the null hypothesis of linearity versus a specified nonlinear alternative, that of a (Logistic) Smooth Transition Vector AutoRegression with a single transition variable. In performing this multivariate test, we consider our vector of endogenous variables X_t. Both tests suggest a clear rejection of the null hypothesis of linearity. Technical details on these tests and their implementation are reported in the Appendix.

The identification of exogenous variations of the uncertainty index is achieved via the widely adopted Cholesky-assumption. Given the ordering of the variables in $\boldsymbol{X}_t$, this implies that we allow for on-impact macroeconomic effects by our identified uncertainty shocks. One of our robustness checks (presented in the next Section) deals with a different ordering of our variables with uncertainty ordered last. The estimates on the macroeconomic effects of uncertainty shocks in recessions turn out to be robust to this alternative ordering.[9]

[8] The plot of the series is provided in the Appendix. Following the recent macroeconomic literature, we model the unemployment rate in levels. For a univariate analysis focusing on a logistic transformation of the unemployment rate and confirming the superiority of a non-linear threshold model, see Koop and Potter (1999).

[9] In our VAR, uncertainty is captured by the VIX, which is a "second moment" by construction.

A key-role is played by the transition variable z_t. Following Auerbach and Gorodnichenko (2012) and Bachmann and Sims (2012), we employ a standardized backward-looking moving average involving seven realizations of the real GDP quarter-on-quarter percentage growth rate.[10] Granger and Teräsvirta (1993) suggest to fix γ to ease the estimation of the remaining parameters of highly non-linear STVARs like ours. We calibrate the smoothness parameter γ by referring to the duration of recessions in the U.S. according to the NBER business cycle dates (17% percentage of the time in our sample according to the dating proposed by the NBER). Then, we define as "recession" a period in which $F(z_t) \geqslant 0.83$, and calibrate γ to obtain $\Pr(F(z_t) \geqslant 0.83) \approx 0.17$. This metric implies a calibration $\gamma = 1.75$, which is quite close to the 1.5 value employed by Auerbach and Gorodnichenko (2012) and Bachmann and Sims (2012).[11]

Our transition function $F(z_t)$ is shown in Figure 1.[12] Clearly, high realizations of $F(z_t)$ tend to be associated with NBER recessions. Notice that the a priori choice of a transition function provides us with an information that we would otherwise need to recover from the data by estimating a latent factor dictating the switch from a state to another, as it occurs when Markov-Switching VAR frameworks are taken to the data.

The (linear/non-linear) VAR feature three lags. This choice is justified by the Akaike criteria when applied to a linear model estimated on the full-sample 1962Q3-2012Q3. Results are robust to reasonable variations of the number of lags (results available upon request).

Given the high non-linearity of the model, we estimate it by Monte-Carlo Markov-Chain simulations. The Appendix reports details on the estimation methodology.[13] Notice that the indicator variable z_t is not embedded in our vector of modeled variables

Differently, we do not model the evolution of the second moments of other structural shocks in our vector. We notice, however, that our VAR features a time-varying covariance matrix of its residuals. Most likely, this captures the bulk of the volatility of the structural shocks other than the uncertainty shock. Hence, while in principle our "uncertainty shock" might pick up some unmodeled volatility of the remaining structural shocks, this case is likely to be negligible from an empirical standpoint.

[10] The transition variable z_t is standardized to render our calibration of the slope parameter γ comparable to the ones employed in the literature.

[11] This implies labeling as "recessions" periods in which $z_t \leq -0.91$. This is equivalent to assuming a threshold value $\overline{z} = -0.91$ for the transition function $F(\widetilde{z}_t)$, with $\widetilde{z}_t \equiv z_t - \overline{z}$. Accordingly, a recession is a phase in which $F(\widetilde{z}_t) \geqslant 0.5$, which takes place when $z_t \leq \overline{z}$.

[12] The Appendix shows that our transition function $F(z_t)$ is extremely close to that employed in Auerbach and Gorodnichenko (2012) and Bachmann and Sims (2012).

[13] Note that, in principle, this model could be estimated by maximum-likelihood. However, as pointed out by Teräsvirta and Yang (2013), finding the optimum of the target function may be problematic due to its flatness in some directions and its many local optima. An alternative to the MCMC pursued in our paper is the search of a suitable starting value of the vector of parameters of interest (Teräsvirta and Yang, 2013).

$\boldsymbol{X}_t$. As discussed in Koop, Pesaran, and Potter (1996), absent any feedback from the endogenous variables to z_t, we can compute the impulse responses to an uncertainty shock by assuming regime-specific linear VARs. In other words, we will compute the macroeconomic reactions to uncertainty shocks by assuming to start in a recession and to remain in such state, i.e., we assign a zero-probability to switch to a non-recessionary phase. This choice is justified by our interest to focus on the short-run dynamics of the U.S. economic system. Moreover, this choice has some desirable implications, i.e., the impulse responses will depend neither on initial conditions nor on the size or sign of the uncertainty shock. To give some statistical support to our choice, we regress the estimated uncertainty shocks (conditional on our linear VAR) on a constant and three lags of the transition variable. The p-value associated to F-test on the predictive power of real GDP growth as for future uncertainty shocks reads 0.10. The reason of the weak-to-nil predictive power of the transition variable is the presence of the unemployment rate in our VAR. We corroborate this hypothesis by estimating an uncertainty shocks with a trivariate VAR featuring uncertainty, inflation, and the federal funds rate only. When regressing the uncertainty 'shock' obtained with this VAR without unemployment, the p-value turns out to be 0.03, an evidence supporting our conjecture on the informativeness of the unemployment rate in our VAR.

It is worth stressing that our STVAR framework exploits information coming from all the observations in the dataset, which are "indexed" by the transition function $F(z_t)$. Differently, the estimation of two different VAR models (one for each given regime) would imply more imprecise estimates due to the smaller number of observations, especially for recessionary periods.

2.2 Focus on recessions

The focus of our analysis is on recessions. Two reasons lie behind this choice. First, peaks in uncertainty measures often occur during recessions. Differently, expansionary phases are characterized by "heterogeneous signals" associated with any measure of uncertainty (e.g. high vs. low realizations with respect to their sample means). Figure 2 plots four indicators of uncertainty often employed in empirical studies, i.e., the VIX (a volatility index related to the U.S. stock market), widely used as a proxy for uncertainty at a macroeconomic level (e.g., Bloom, 2009, Leduc and Liu, 2013); a common macro uncertainty factor estimated by Jurado, Ludvigson, and Ng (2013), which is a factor modeling the one-year ahead forecast error related to a large dataset of

U.S. data; the Corporate Bond Spread (computed as the difference between the Baa 30 year-yield and the Treasury yield at a comparable maturity), employed by Bachmann, Elstner, and Sims (2013); and the Economic Policy Uncertainty index developed by Baker, Bloom, and Davis (2013), which is based on information coming from a set of U.S. newspapers and survey data. The evolution of these indicators confirms that recessions, as identified by the NBER, are characterized by comovements in the same direction of all measures of uncertainty. In contrast, ups and downs of these indicators are far from being rare during NBER expansions. Hence, a priori, recessions seem to carry cleaner information on the effects of uncertainty shocks on the macroeconomic environment than expansions. A formal support to this intuitive position is offered by a recent work by Jurado, Ludvigson, and Ng (2013), who carefully develop uncertainty factors by modeling the variability of the purely unforecastable components of future values of a large set of economic indicators. Their estimated uncertainty factors are shown to peak in correspondence to three big post-WWII recessions (1973-74, 1981-82, 2007-2009). More generally, they find macro uncertainty to be higher in recessions than in non-recessions years. Moreover, while the identification of recessions appears to be uncontroversial in the literature, the identification of expansionary phases has proved to be debatable. In particular, the traditional two state-classification of the U.S. business cycle based on the identification of recessions and expansions has been challenged by, among others, Sichel (1994), van Dijk and Franses (1999), Galvão (2002), and Morley, Piger, and Tien (2012). These authors have uncovered different dynamics of business cycle indicators during "non-recessionary" phases, which have led them to model the U.S. economy with more than two states. These considerations motivate our focus on recessions.[14]

3 Results

Figure 3 plots the estimated dynamic responses to a one standard deviation-shock to uncertainty (here approximated with the VIX) conditional on a linear formulation of our VAR. The reaction of inflation is short lived and not significant at a 90% confidence level (although clearly significant at a 68% one), and points to a deflationary phase in the aftermath of the shock. Unemployment increases significantly and persistently, and follows a hump-shaped path before going back to its steady-state value. The policy rate

[14] Given our focus on recession, we do not explicitly model the non-recessionary phases. Implicitly, we assume that our results conditional on recessions are not affected by this choice.

decreases significantly and persistently after the shock, following a pattern consistent with a flexible inflation targeting strategy by the Federal Reserve. These results are in line with those obtained by Leduc and Liu (2013), i.e., our linear model suggests that aggregate uncertainty shocks act as "demand" shocks in the sense that they temporarily open a recession and lower inflation.[15]

A *quantitatively* very different picture emerges when non-linearities are admitted to play a role in this system. Figure 4 superimposes the dynamic responses conditional on a recessionary phase of the economy to those estimated with the linear framework. Several elements are worth noting. First, the reaction of unemployment is much larger during recession. The linear VAR model predicts that an exogenous increase of the VIX may be followed by a reaction of the unemployment rate of about 0.17 percentage points four quarters after the shock, and of about 0.15 percentage points eight quarters after such shock. The non-linear VAR reveals that the same shock, when hitting the economic system during a recession, is estimated to induce an increase of unemployment of 0.38 percentage points four quarters after the shock, and 0.47 two years after the shock. The difference is statistically significant. This suggests that uncertainty shocks may exert quite a severe impact on unemployment when the economy is already experiencing a recession. Somewhat not surprisingly (in light of a possible Phillips curve-related reading of U.S. inflation dynamics), the reaction of price inflation is also predicted to be larger after the shock. As in the linear case, monetary policy (whose stance is here captured by the federal funds rate) reacts according to an inflation targeting strategy. Similarly to inflation and unemployment, the federal funds rate is estimated to be more sensitive to uncertainty shocks during recessions.[16]

From a modeling standpoint, the non-linear VAR suggests that the relative force of different transmission channels may change over the business cycle. The overall effect on the real side of the economy and inflation is negative during recessions as well as

[15] A note of caution on the identification of uncertainty shocks is due here. As stressed by Stock and Watson (2012), uncertainty shocks and liquidity/financial risk shocks are highly correlated, which makes their separate interpretation problematic. Christiano, Motto, and Rostagno (2013) propose a model to interpret the causal role that a measure of risk may play in influencing credit spreads. Following the recent VAR literature, our "uncertainty shocks" are to be interpreted as exogenous variations of an empirical proxy for uncertainty in our VARs.

[16] Admittedly, the differences between the responses based on our linear VAR and those associated to recessions are likely to be over-estimated by the assumption of no change of the very strong recessionary phase we focus on. One should therefore interpret the estimated responses under recessions as a upper bound, more than a mean estimate. On the other hand, the coefficients of our recessions-related VAR are estimated by using also information about the dynamics of the system in the non-recessionary regime, a strategy which is likely to bias the non-linear estimates towards those associated to the linear VAR.

according to the linear model. This evidence is replicable by a model featuring matching frictions in the labor market as shown by Leduc and Liu (2013), who also discuss how price stickiness may magnify the demand effects of uncertainty shocks. The quantitative difference found between our two sets of impulse responses may therefore be due to a larger impact exerted by real frictions on the labor market during recessions (e.g., lower likelihood to form a firm-worker match, higher probability of breaking a previously formed-match). Differently, our results cast doubts on pure RBC frameworks featuring a Walrasian labor market. In such models, uncertainty shocks generate expansions due to their effects on labor supply, which raises the level of potential output. Our analysis solidly rejects the prediction of expansionary uncertainty shocks both with linear models and with non-linear frameworks.

4 Robustness checks

The baseline exercises suggest that uncertainty shocks are important for the U.S. unemployment dynamics. However, these results may be spurious if caused by misspecification of the econometric model. If our VAR does not embed sufficient information to consistently estimate the uncertainty shocks, the impulse responses could be distorted and, possibly, spuriously magnify the role of such shocks. Variables endowed with relevant information for modeling the shock of interest and/or the interactions among the variables may be omitted from the VAR. Several examples of potentially relevant but omitted variables are provided by the literature. For instance, consumer sentiment may be important for explaining households' decisions and influence labor supply, therefore affecting production and unemployment. VARs may also miss to consider anticipated effects of uncertainty shocks. Christiano, Motto, and Rostagno (2013) show that, in an estimated DSGE model of the business cycle with a number of real, nominal, and financial frictions, anticipated risk (uncertainty) shocks (measured as the evolution of cross-sectional dispersion of firms' capital efficiency) greatly improve their model's descriptive power. This implies that VAR one-step ahead forecast errors of empirical measures of uncertainty may confound unexpected movements of the level of uncertainty with expected ones. Both the first and the second type of informational insufficiency may be tackled by expanding our baseline vector to include possibly omitted variables for better capturing the correlations in the data as well as for modeling agents' expectations over future (and known) realizations of the relevant shocks. Another issue regards our identification strategy, which relies on a Cholesky decomposition conditional on a vector with uncertainty ordered first. Despite being quite popular in the literature, this assumption is debatable. We check the robustness of our results to various perturbations of the baseline vector. Such perturbations are presented and motivated below.

S&P500. Our baseline analysis identifies uncertainty shocks by isolating exogenous movements of the VIX. Such index captures the *volatility* of the stock market. Of course, variations of the *level* of the stock market *per se* may be important determinant of the aggregate demand and inflation (for instance, because of financial wealth-related effects in a sticky-price context as in Castelnuovo and Nisticò, 2010). In our sample, the correlation between the VIX and the log of the S&P500 is 0.28. Hence, the risk here is to confound variations in uncertainty with variations in the level of the stock market index. We then consider the five-variate VAR $\boldsymbol{X}_t^{s\&p500} = [S\&P500_t, vix_t, \pi_t, un_t, R_t]'$, where "$S\&P500$" captures the log of S&P500 (source: Federal Reserve Bank of St. Louis' website).[17]

TFP. Bachmann and Bayer (2013) propose a model in which shocks to firms' profitability risk, propagated via capital adjustment costs, have the potential to be a major source of business cycle fluctuations. Using a rich German firm-level dataset, they find that such a shock, when taken in isolation, leads firms to adopt a "wait-and-see" strategy for investment. However, the contribution of this shock to the forecast error variance of investment, output, and total hours is found to be limited. Interestingly, the micro-data employed by Bachmann and Bayer (2013) support a version of the model in which aggregate productivity and firm-level risk processes are correlated. In presence of this correlation, shocks to firm's profitability risk explain about one-third of the forecast error variance of output (as well as investment and hours) after ten years. This may be due to the fact that risk shocks today anticipate the future evolution of aggregate productivity, whose systematic impact on output and investment is large. Controlling for movements in TFP is therefore important to isolate the role of uncertainty shocks *per se*. We then consider the five-variate VAR $\boldsymbol{X}_t^{TFP} = [TFP_t, vix_t, \pi_t, un_t, R_t]'$, where "$TFP$" is the log of the total factor productivity measure proposed by Fernald (2012). The series we use is adjusted to control for variations in factor utilization as in Basu, Fernald, and Kimball (2006). The source of the data is the Federal Reserve Bank of

[17] The S&P500 displays a distinct up-trending behavior in the sample. We estimate our VAR by employing a cubically detrended measure of (the log of) S&P500. Bloom (2009) and Jurado, Ludvigson, and Ng (2013) Hodrick-Prescott filter the log of the S&P500 index to isolate its cyclical component. Our results are similar when a Hodrick-Prescott filter (smoothing weight: 1,600) is applied to the stock market index.

San Francisco's website.[18]

Consumer sentiment. Uncertainty and consumer confidence also go hand-in-hand, and share some information concerning agents' expectations over the future evolution of the economic system. An often employed measure of consumer sentiment is the index of consumer expectations based on information collected via the Michigan Survey of Consumers. The index is calculated as an average of the results coming from three different questions concerning the future evolution of the business cycle (expectations about aggregate business conditions over the next year; expectations about aggregate business conditions over the next five years; expectations about personal financial conditions over the next year).[19] Bachmann and Sims (2012) estimate the systematic effects due to this measure of consumer "confidence" for the transmission of fiscal policy shocks to the business cycle and find it to be substantial, especially during recessions. The correlation between the VIX and this measure of confidence equals -0.29 in our sample. Hence, once may fear that our uncertainty shocks may proxy confidence shocks, rather than representing genuine exogenous variations of uncertainty. We scrutinize this issue by estimating the five-variate VAR $\boldsymbol{X}_t^{sent} = [sent_t, vix_t, \pi_t, un_t, R_t]'$, where "$sent$" stands for consumer sentiment.[20]

FAVAR. A way to tackle the informational insufficiency issue, popularized by Bernanke, Boivin, and Eliasz (2005), is to add a factor extracted from a large dataset to our VAR, so to purge the (possibly bias-contaminated) estimated shocks. We then consider a large dataset composed of 150 time-series, and extract the common factors which maximize the explained variance of such series (some information on the series of our dataset, their transformations, and the computation of the factors is provided in our Appendix). Our estimation leads us to obtain six common factors, a number equivalent to the one found by Stock and Watson (2012) in their recent analysis on the drivers of the post-WWII U.S. economy. We then conduct a check with the Factor-Augmented Smooth-Transition VAR $\boldsymbol{X}_t^{favar} = [f_t^1, vix_t, \pi_t, un_t, R_t]'$, where "$f_t^1$" is the factor explaining the largest share of variance of the series in our enlarged database.[21]

[18] Following Bachmann and Bayer (2013), we use a linearly detrended measure of (the log of) TFP. An exercise conducted with a Hodrick-Prescott filtered measures (smoothing weight: 1,600) returns very similar results.

[19] Information on the Thomson Reuters/University of Michigan Surveys of Consumers can be found at the URL http://www.sca.isr.umich.edu/main.php.

[20] Bachmann, Elstner, and Sims (2013) employ a measure of business confidence to control for the role of expectations (first moment). Our results are robust to the use of business confidence (as opposed to consumer confidence).

[21] Our first factor is just mildly correlated with the unemployment rate (-0.02). Therefore, it is likely not to represent a "redundant" variable in our VAR. Notice that, in line with a Okun's law

Cholesky ordering. Finally, our assumptions to identify an exogenous variation of uncertainty implies that no macroeconomic shock can contemporaneously affect the level of uncertainty in the economic system. While being common in this literature, the assumption is nonetheless questionable. To check the extent to which this assumption may affect our results, we run a set of estimates by ordering uncertainty last in our vector, i.e., $\boldsymbol{X}_t^{unclast} = [\pi_t, un_t, R_t, vix_t]'$. This alternative ordering allows us to "purge" the VIX by the movements due to past as well as contemporaneous shocks hitting the economic system. By construction, we force the macroeconomic variables modeled with our VAR to have a zero on-impact reaction to uncertainty shocks.

The outcome of all robustness checks are reported in Figure 5. In all cases, we find a recessionary evolution of the unemployment rate comparable to the baseline case. Admittedly, some quantitative effects are present. The vectors featuring either the measure of TFP, the factor, or the measure of consumer confidence predict a somewhat milder response of unemployment with respect to the baseline case. The vector controlling for movements in the S&P500 index returns an even milder (but still quite substantial) short-run response of unemployment. However, as a matter of fact, all scenarios confirm the remarkable increase of unemployment in response to an uncertainty shock. The response of inflation turns out to be quite robust across scenarios, with a clear and abrupt fall in the short-run and a fairly quick rebound. The response of the policy rate is estimated to be extremely robust as well.[22]

Importantly, the role of non-linearities turns out to be supported also by our sensitivity analysis. Figure 6 shows the difference between the predictions of linear vs. non-linear VARs in each of the cases previously shown in Figure 5. In particular, it focuses on the two policy-relevant variables in our analysis, i.e., unemployment and inflation. While some heterogeneity across scenarios may be detected, all cases under scrutiny point to a substantially deeper recession and deflationary phase after a shock when non-linearities are taken into account, and recessions are the focus of our

interpretation of the relationship between real GDP and unemployment, the correlation between the first factor (whose degree of correlation with the real GDP growth rate reads 0.73) and the *difference* in the unemployment rate is much stronger (-0.72).

[22] Bachmann and Bayer (2013) show that most of the relevance of firm-level risk shocks is due to their systematic interaction with aggregate productivity. Our results are confirmed by an exercise in which the systematic impact of uncertainty shocks on TFP is set to zero in the VAR. Admittedly, the discrepancy between our results and Bachmann and Bayer's (2013) may be due to the inability of our VAR to correctly capture the "structural" correlation between risk and aggregate productivity. Moreover, our measure of *aggregate* uncertainty differs from Bachmann and Bayer's, which is constructed with a detailed dataset referring to German firms. We leave the exploration of the relationships among firm risk, aggregate uncertainty, and aggregate productivity to future research.

investigation. Quantitatively, the indications coming from the VARs are very similar.[23]

Uncertainty shocks and non-recessionary phases. Are recessions really of help to identify the effects of uncertainty shocks? Figure 7 plots the results obtained by focusing on *non-recessionary* phases. The main message is that variations of the information set embedded in the vectors, as well as of our identification schemes, importantly affect the estimated impulse responses of the different models. Substantially different indications arise regarding not only the magnitude of the macroeconomic responses, but also their sign. In particular, the FAVAR model predicts a negative (and substantially so) reaction of inflation, as in recessionary phases. This goes in contrast with the baseline analysis, which suggests a positive reaction of price inflation to an exogenous increase in uncertainty. Such a positive reaction may be due to workers' bargaining power over nominal wages in periods of economic expansions, which call for an optimal increase in the price level by firms that target a desired mark-up (Mumtaz and Theodoridis, 2012).[24] A mild and statistically non significant decrease in inflation is predicted by the four-variate VAR in which uncertainty is ordered last. The zero-initial condition imposed by our Cholesky identification scheme can be a possible explanation of the mild response of inflation, at least in the short-run. More importantly for our research question, unemployment is also predicted to respond differently by our different VARs. The "uncertainty last" scenario returns a hump-shaped reaction quite similar (at least, qualitatively) to those shown during recessions. The other scenarios (except the FAVAR) predict a statistically insignificant response of unemployment the first two years after the shock, and an increase in unemployment after. Differently, the FAVAR predicts an economic boom (a decrease in unemployment). In light of this different predictions, it is not surprising that the paths of the policy rate implied by our VARs are also scenario-specific.

Comparing the impulse responses of Figure 7 to those plotted in Figures 5 and 6 highlights how the fragility of our results conditional on non-recessionary phases stands in stark contrast with the robustness of the responses conditional on recessions. Our interpretation of this difference in robustness is the "weak-identification issue" affecting uncertainty shocks in non-recessionary phases. As previously discussed, recessions are

[23] Our results are also robust to the inclusion of oil prices in the vector (results available upon request).

[24] Interestingly, the uncertainty surrounding the responses of our baseline vector is larger than the one surrounding the responses estimated conditional on recessions. This occurs in spite of the much larger number of non-recessionary observations in our sample. We interpret this evidence as, once again, a consequence of weak identification of uncertainty shocks in non-recessionary phases of the business cycle.

likely to be much more informative to identify disturbances such as uncertainty shocks, and the presence of a small set of macroeconomic indicators is enough to extract the exogenous component from the VIX and study its (quite clear) macroeconomic effects. Viceversa, the effects of uncertainty shocks during non-recessionary phases are likely to be much milder (if not present at all) and more difficult to identify. Therefore, variations of the information set available to the econometrician to pin such effects down may importantly affect the estimated dynamic responses. We take this evidence as supportive of the ability of our VARs to identify uncertainty shocks and their effects during recessions, and of our choice of focusing on recessions.

Different measures of uncertainty. So far, the analysis has hinged upon the VIX as a proxy of the macroeconomic uncertainty affecting the economic system. As discussed in Section 2, alternative proxies for uncertainty have been proposed by the literature. Jurado, Ludvigson, and Ng (2013) compute a macro uncertainty factor by modeling the common component of n-step ahead forecast error variances of 132 macroeconomic series.[25]Bachmann, Elstner, and Sims (2013) consider the Corporate Bond Spread (computed as the difference between the Baa 30 year-yield and the Treasury yield at a comparable maturity). We re-run our estimates by replacing the VIX with these two measures of uncertainty (employed one at a time). As in the baseline scenario, we consider the effects of a standard deviation innovation to uncertainty.

Figure 8 compares the baseline results with those obtained with the two alternative measures of uncertainty. The responses are somewhat different from a quantitative standpoint, a fact that confirms the different information content carried by these indicators of uncertainty. In particular, the response of inflation to the Corporate Bond spread is estimated to be more accentuated than the baseline one, while that of unemployment slightly less large. The reaction of unemployment to unexpected movements in the common factor computed by Jurado, Ludvigson, and Ng (2013) is quite similar to our baseline result. From a qualitative standpoint, all three indicators of uncertainty point to the same evidence, i.e., uncertainty hikes open a persistent recession and a deflation, therefore acting as a demand shock. In this sense, our non-linear analysis offers solid support to Leduc and Liu's (2013) prediction on the effects of uncertainty

[25]Jurado, Ludvigson, and Ng (2013) use the method of diffusion index forecast (a forecasting model with predictors that span a rich information set) to compute the forecast errors of the 132 macroeconomic series of interest, and employ a stochastic volatility model to compute the variance of such forecast errors. As a measure of macro uncertainty, we take the common factor they computed conditional on the one year-ahead forecast error variances. The factors computed by Jurado, Ludvigson, and Ng (2013) with the large dataset of macro series are monthly. We create quarterly observations by taking within-quarter averages.

on unemployment.

5 Are uncertainty shocks economically relevant? Welfare costs, FEVDs

The previous Section established the *statistical* difference between the responses to uncertainty shocks of inflation, unemployment, and the federal funds rate computed with a linear VAR and those obtained with a non-linear STVAR framework. How relevant is this difference from an *economic* standpoint? To answer this question, we employ an operational loss function à la Sala, Söderström, and Trigari (2008). These authors deal with a micro-founded model featuring relevant frictions on the labor market. Their computation of the optimal monetary policy in presence of such frictions involves the following loss function:

$$L = \sigma_\pi^2 + \lambda_u \sigma_u^2 + \lambda_i \sigma_i^2 \tag{5}$$

where $\sigma_j^2, j = \pi, u, i$ identify the volatilities (variances) of key-macroeconomic indicators, and $\lambda_j, j = u, i$ the relative weights assigned to the volatility of unemployment and the nominal interest rate, respectively.[26] We work with eq. (5) and employ the impulse responses to compute the macroeconomic volatilities *conditional to an uncertainty shock* with a linear vs. non-linear model during recessions. In order to limit the impact of the "tail estimates" of our responses, which may be imprecisely estimated and contaminate our results, we focus on the first 12 quarters after the shock.

To assess the relevance of non-linearities, we compute the percentage deviation of the loss L^{REC} obtained with the non-linear model with respect to the loss L^{LIN} obtained with the linear VAR:

$$PD = 100 \left(\frac{L^{REC}}{L^{LIN}} - 1 \right)$$

The value of such percentage deviation depends on the relative weights employed in the loss function. We control for the role played by these weights in the computation of the losses by considering the following ranges: $\lambda_u \in [0, 1]$, $\lambda_i \in [0, 0.25]$.

[26] Sala, Söderström, and Trigari (2008) consider a loss function featuring the unemployment gap, i.e., the difference between the unemployment rate and its natural counterpart. Our VARs do not model the NAIRU. Hence, we approximate the unemployment gap with the unemployment rate, the implicit assumption being that of a relatively constant NAIRU over the sample.

Figure 9 plots the surface obtained by considering several different combination of weights λ_j. A clear message arises. The welfare costs estimated with a non-linear model are at least three times as large as those computed with a linear framework. The gap increases when a positive weight is assigned to the volatility of unemployment and/or to that of the interest rate. Hence, the difference in the impulse responses shown in the previous Section are not only statistically relevant, but also economically important.

Finally, we assess the contribution of uncertainty shocks for the dynamics of the variables of interest by performing a forecast error variance decomposition. Table 1 collects figures concerning our eight quarter-ahead investigation. Conditional on the linear VAR, uncertainty shocks are estimated to be responsible for an important share of the variance of unemployment (23%), and a negligible one as for inflation (1%) and the policy rate (2%). Quite differently, conditional on recessions uncertainty shocks contribute three times as much to the variance of unemployment (62%), and explain a substantial chunk of the variance of the policy rate (41%). The contribution of inflation is also much larger (8%) than estimated with a linear model.

To appreciate the role of uncertainty shocks, Table 1 also reports the estimated contribution of monetary policy shocks, which are identified with a standard Cholesky scheme. The linear model suggests a large contribution to the variance of the policy rate (49%), and a moderate one as for unemployment (5%) and inflation (1%). The non-linear model predicts a milder contribution of policy shocks on unemployment (1%). Some lessons can be drawn from this variance decomposition analysis. First, uncertainty shocks importantly contribute to the dynamics of unemployment in recessions. Second, linear models may lead to an underestimation of the contribution of uncertainty shocks, a finding in line with our impulse response function analysis. Third, uncertainty shocks turn out to be more important than monetary policy shocks in explaining the dynamics of unemployment. Incidentally, we notice that monetary policy shocks are estimated to be more powerful (as for their effects on unemployment) in "normal times" (here approximated by our linear model, which mixes up recessions and non-recessionary phases) than during recessions. This finding lines up with the recent empirical analysis by Aastveit, Natvik, and Sola (2013), who document a weaker effect of monetary policy shocks in phases of high uncertainty.

One potential issue to take into account is that the estimated contribution of uncertainty shocks to the variance of the forecast error of unemployment might be biased due to the lack of relevant information in our baseline VAR. We then implement the same exercise with our five-variate model with S&P500. Table 2 collects the contribution of uncertainty shocks conditional on this enriched model, and contrast them to those shown in Table 1. Perhaps not surprisingly, the five-variate VAR suggests a substantially lower contribution of uncertainty shocks during recessions (10%). However, the non-linear model confirms, once again, a much more important role for uncertainty shocks than what suggested by a standard linear VAR (2%).[27]

6 Conclusions

We investigate the macroeconomic effects of uncertainty shocks in the post-WWII U.S. economy with linear and non-linear (Smooth-Transition) VARs. We find such effects to be asymmetric over the business cycle. In particular, the response of unemployment conditional on recessions is documented to be substantially larger than the one predicted by a linear VAR model. We also find a stronger reactiveness of inflation during economic downturns. Such differences are shown to be robust to a variety of perturbations of our baseline vector, including different information sets, alternative measures of uncertainty, and different strategies to identify uncertainty shocks in the VARs. The computation of the welfare costs conditional on uncertainty shocks, implemented with an operational loss function, confirms that linear models confounding recessions and non-recessionary phases may substantially downplay the costs triggered by uncertainty shocks. From a modeling standpoint, our results support the modeling of real frictions on the labor market, which have been previously shown to be key for replicating the response of unemployment to uncertainty hikes, above all when combined with nominal price frictions (Leduc and Liu, 2013).

From a policy perspective, our findings suggest that uncertainty shocks may be substantially more costly than we think. What can policymakers do to reduce uncertainty-related costs? Baker, Bloom, and Davis (2013) develop a novel indicator of economic policy uncertainty, i.e., future policy moves that are perceived to be surrounded by uncertainty by the U.S. households. Interestingly, the correlation between Baker et al.'s (2013) index and those employed in this study ranges from 0.40 (with the common factor estimated by Jurado, Ludvigson, and Ng, 2013) to 0.52 (with the VIX). We believe that our findings provide support to the research agenda recently launched by Bloom

[27] The same exercise conducted with our FAVAR model returns qualitatively similar results. In particular, uncertainty shocks are estimated to exert a very mild contribution to the forecast error variances of inflation and the policy rate (1%), and a moderate contribution to unemployment rate's forecast error variance (10%). Differently, the figures under recessions read 6% (inflation), 26% (unemployment rate), and 31% (policy rate).

(2009) on the policy trade-off between "correctness" and "decisiveness". Is it better to act decisively (but occasionally incorrectly) than to deliberate on policy, with the risk of generating policy-induced uncertainty? In light of our results, this appears to be a well-worth investigating research question.

References

Aastveit, K. A., G. J. Natvik, and S. Sola (2013): "Macroeconomic Uncertainty and the Effectiveness of Monetary Policy," Norges Bank, mimeo.

Alexopoulos, M., and J. Cohen (2009): "Uncertain Times, Uncertain Measures," University of Toronto, Department of Economics Working Paper No. 325.

Auerbach, A., and Y. Gorodnichenko (2012): "Measuring the Output Responses to Fiscal Policy," *American Economic Journal: Economic Policy*, 4(2), 1–27.

Bachmann, R., and C. Bayer (2013): ""Wait-and-See" Business Cycles," *Journal of Monetary Economics*, forthcoming.

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

Bachmann, R., and G. Moscarini (2012): "Business Cycles and Endogenous Uncertainty," RWTH Aachen University and Yale University, mimeo.

Bachmann, R., and E. Sims (2012): "Confidence and the transmission of government spending shocks," *Journal of Monetary Economics*, 59, 235–249.

Baker, S., and N. Bloom (2012): "Does Uncertainty Reduce Growth? Using Disasters As Natural Experiments," Stanford University, mimeo.

Baker, S., N. Bloom, and S. J. Davis (2013): "Measuring Economic Policy Uncertainty," Stanford University and the University of Chicago Booth School of Business, mimeo.

Basu, S., and B. Bundick (2011): "Uncertainty Shocks in a Model of Effective Demand," Boston College, mimeo.

Basu, S., J. Fernald, and M. Kimball (2006): "Are Technology Improvements Contractionary?," *American Economic Review*, 96, 1418–1448.

Beetsma, R., and M. Giuliodori (2012): "The changing macroeconomic response to stock market volatility shocks," *Journal of Macroeconomics*, 34, 281–293.

Benigno, G., P. Benigno, and S. Nisticò (2012): "Risk, Monetary Policy and the Exchange Rate," NBER Macroeconomics Annual, 26, 247–309.

Bernanke, B., J. Boivin, and P. Eliasz (2005): "Measuring Monetary Policy: A Factor Augmented Vector Autoregressive (FAVAR) Approach," *Quarterly Journal of Economics*, 120(1), 387–422.

Bianchi, F., and L. Melosi (2013): “Dormant Shocks and Fiscal Virtue,” NBER Macroeconomics Annual, forthcoming.

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

Bloom, N., J. Fernández-Villaverde, and M. Schneider (2013): “The Macroeconomics of Uncertainty and Volatility,” *Journal of Economic Literature*, in preparation.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. J. Terry (2012): “Really Uncertain Business Cycles,” NBER Working Paper Series, Working Paper No. 18245.

Castelnuovo, E., and S. Nisticò (2010): “Stock Market Conditions and Monetary Policy in a DSGE Model for the U.S.,” *Journal of Economic Dynamics and Control*, 34(9), 1700–1731.

Christiano, L., R. Motto, and M. Rostagno (2013): “Risk Shocks,” *American Economic Review*, forthcoming.

Colombo, V. (2013): “Economic policy uncertainty in the US: Does it matter for the Euro Area?,” *Economics Letters*, forthcoming.

Fernald, J. (2012): “A Quarterly, Utilization-Adjusted Series on Total Factor Productivity,” Federal Reserve Bank of San Francisco Working Paper No. 2012-19.

Fernández-Villaverde, J., P. Guerrón-Quintana, J. F. Rubio-Ramírez, and M. Uribe (2011): “Risk Matters: The Real Effects of Volatility Shocks,” *American Economic Review*, 101, 2530–2561.

Galvão, A. B. (2002): “Can non-linear time series models generate US business cycle asymmetric shape?,” *Economics Letters*, 77, 187–194.

Gilchrist, S., J. W. Sim, and E. Zakrajsek (2013): “Uncertainty, Financial Frictions, and Irreversible Investment,” Boston University and Federal Reserve Board, mimeo.

Gilchrist, S., and J. Williams (2005): “Investment, Capacity, and Uncertainty: A Putty-Clay Approach,” *Review of Economic Dynamics*, 8, 1–27.

Granger, C., and T. Teräsvirta (1993): “Modelling Nonlinear Economic Relationships,” Oxford University Press: Oxford.

Jurado, K., S. C. Ludvigson, and S. Ng (2013): “Measuring Uncertainty,” Columbia University, New York University, and NBER, mimeo.

Koop, G., M. Pesaran, and S. Potter (1996): “Impulse response analysis in nonlinear multivariate models,” *Journal of Econometrics*, 74, 119–147.

Koop, G., and S. Potter (1999): “Dynamic Asymmetries in U.S. Unemployment,” *Journal of Business and Economic Statistics*, 17(3), 298–312.

Leduc, S., and Z. Liu (2013): “Uncertainty Shocks are Aggregate Demand Shocks,” Federal Reserve Bank of San Francisco, Working Paper 2012-10.

Luukkonen, R., P. Saikkonen, and T. Teräsvirta (1988): "Testing linearity against smooth transition autoregressive models," *Biometrika*, 75, 491–499.

Morley, J., and J. Piger (2012): "The Asymmetric Business Cycle," *Review of Economics and Statistics*, 94(1), 208–221.

Morley, J., J. Piger, and P.-L. Tien (2012): "Reproducing Business Cycle Features: Are Nonlinear Dynamics a Proxy for Multivariate Information?," *Studies in Nonlinear Dynamics & Econometrics*, forthcoming.

Mumtaz, H., and K. Theodoridis (2012): "The international transmission of volatility shocks: An empirical analysis," Bank of England Working Paper No. 463.

Nodari, G. (2013): "Uncertainty, Financial Regulation and Credit Spreads in the U.S.," University of Padova, mimeo.

Sala, L., U. Söderström, and A. Trigari (2008): "Monetary policy under uncertainty in an estimated model with labor market frictions," *Journal of Monetary Economics*, 55(5), 983–1006.

Sichel, D. E. (1994): "Inventories and the three phases of the business cycle," *Journal of Business and Economics Statistics*, 12, 269–277.

Stock, J. H., and M. W. Watson (2012): "Disentangling the Channels of the 2007-2009 Recession," *Brookings Papers on Economic Activities*, forthcoming.

Teräsvirta, T., and Y. Yang (2013): "Specification, Estimation and Evaluation of Vector Smooth Transition Autoregressive Models with Applications," CREATES, Aaruhs University.

van Dijk, D., and P. H. Franses (1999): "Modeling multiple regimes in the business cycle," *Macroeconomic Dynamics*, 3, 311–340.

van Dijk, D., T. Teräsvirta, and P. H. Franses (2002): "Smooth Transition Autoregressive Models - A Survey of Recent Developments," *Econometric Reviews*, 21(1), 1–47.

Yellen, J. (2013): "Communication in Monetary Policy," speech held at the Society of American Business Editors and Writers 50th Anniversary Conference, Washington D.C, April 4.

Phase/Var.	*inflation*	*unempl*	*pol. rate*
Uncertainty shocks			
Linear	1	23	2
Recession	8	62	41
Monetary policy shocks			
Linear	1	5	49
Recession	1	1	29

Table 1: **Role of uncertainty and monetary policy shocks: 8 quarter-ahead forecast error variance decomposition.** Figures conditional on our baseline VAR. Sample: 1962Q3-2012Q3.

Phase/Var.	*inflation*	*unempl*	*pol. rate*
Baseline model			
Linear	1	23	2
Recession	8	62	41
Five-variate model with S&P500			
Linear	1	2	1
Recession	2	10	6

Table 2: **Role of uncertainty in different models: 8 quarter-ahead forecast error variance decomposition.** Figures conditional on our baseline VAR and our five-variate model with the stock-market index as first variable in the vector. Sample: 1962Q3-2012Q3.

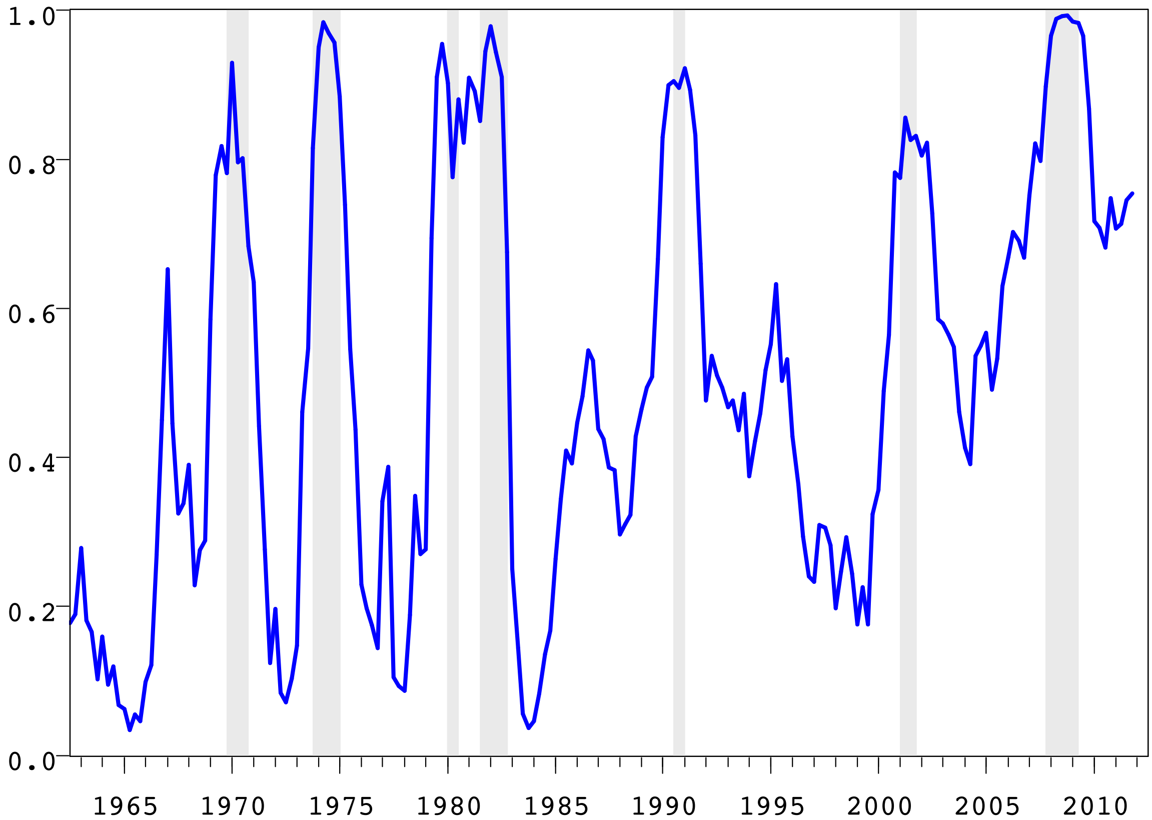

Figure 1: **Probability of being in a recessionary phase.** Blue line: Transition function F(z). Shaded columns: NBER recessions.

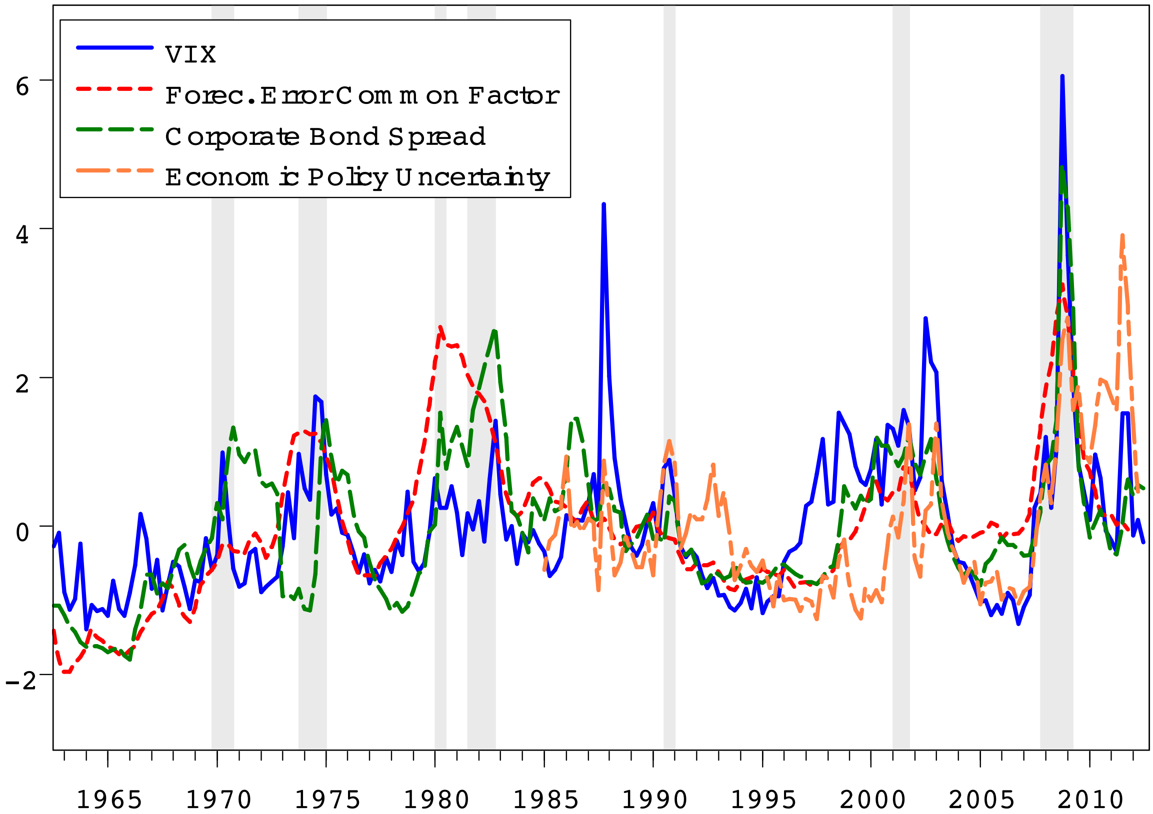

Figure 2: **Uncertainty indicators**. VIX: Volatility IndeX as in Bloom (2009). Forec. Error Common Factor: Common factor of the one-year ahead forecast error variance decomposition as in Jurado, Ludvigson, and Ng (2013). Corporate Bond Spread: Difference between BAA 30 year-yield and 30-year Treasury Bill yield as in Bachmann, Elstner, and Sims (2013). Economic Policy Uncertainty: index developed by Baker, Bloom, and Davis (2013). Sample: 1962Q3-2012Q3. Higher frequency-data transformed into quarterly realizations via within-the-quarter averages. Shaded columns: NBER recessions.

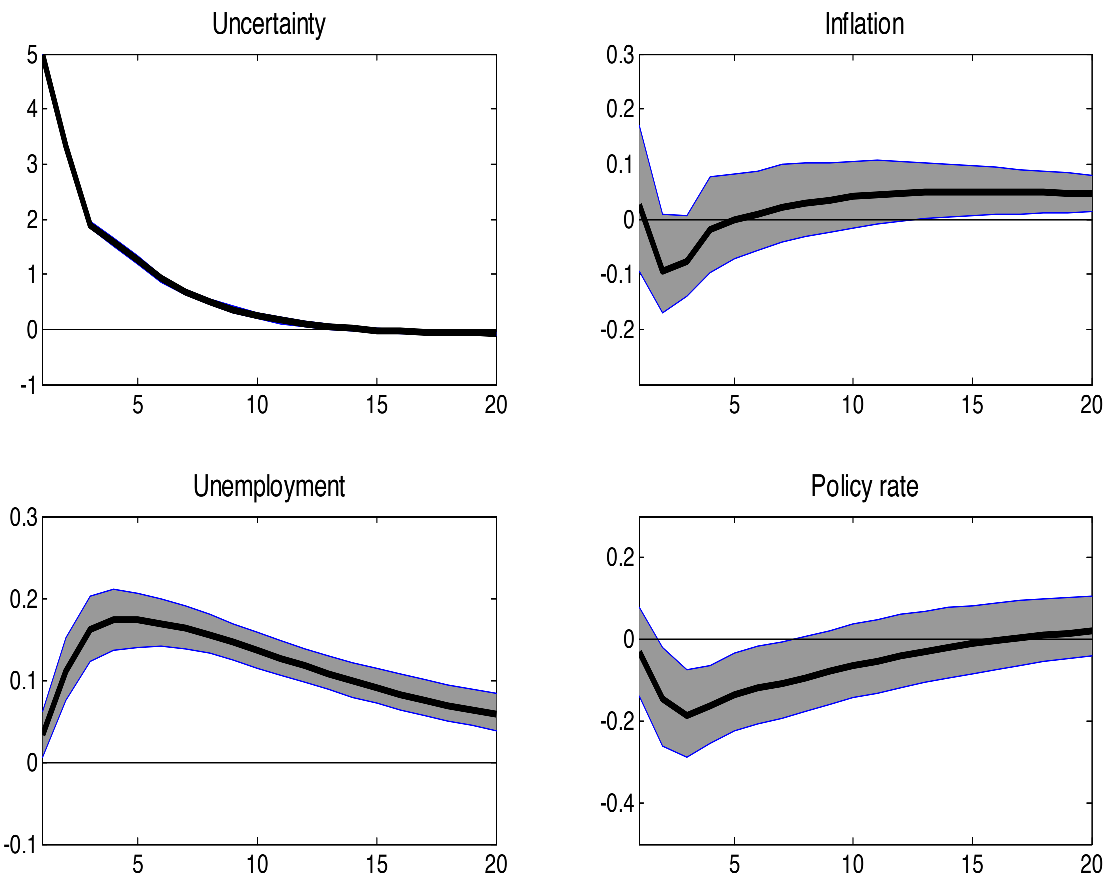

Figure 3: **Macroeconomic effects of uncertainty: Linear VAR**. Effects of a one standard deviation shock to VIX. Sample: 1962Q3-2012Q3. Responses predicted by a linear VAR. Baseline VAR with four variables (uncertainty, inflation, unemployment, policy rate). Gray areas: 90% confidence sets. Shocks identified with a Cholesky-decomposition of the variance-covariance matrix of the reduced-form residuals.

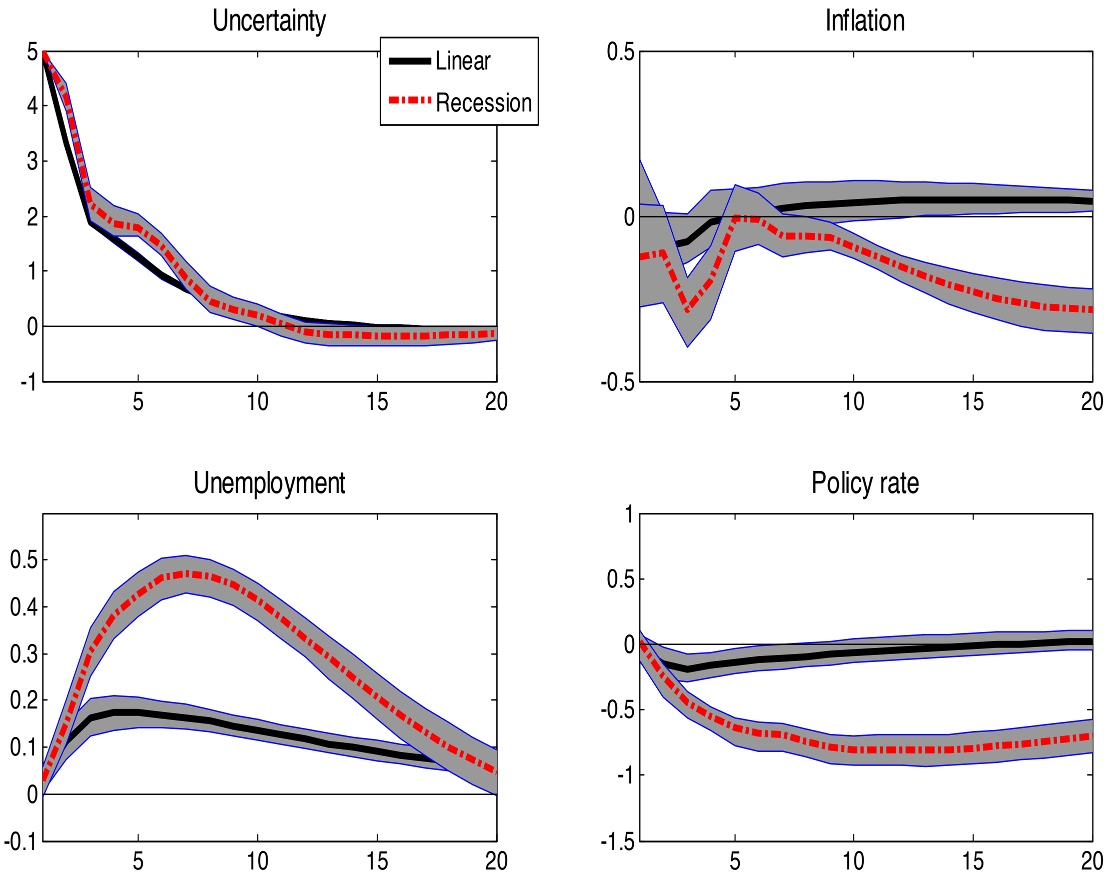

Figure 4: **Macroeconomic effects of uncertainty in recessions**. Effects of a one standard deviation shock to VIX. Sample: 1962Q3-2012Q3. Solid black lines: Responses predicted by a linear VAR. Dash-dotted red lines: Reactions under recessions computed with our non-linear framework. Baseline VAR with four variables (uncertainty, inflation, unemployment, policy rate). Gray areas: 90% confidence sets. Shocks identified with a Cholesky-decomposition of the variance-covariance matrix of the reduced-form residuals.

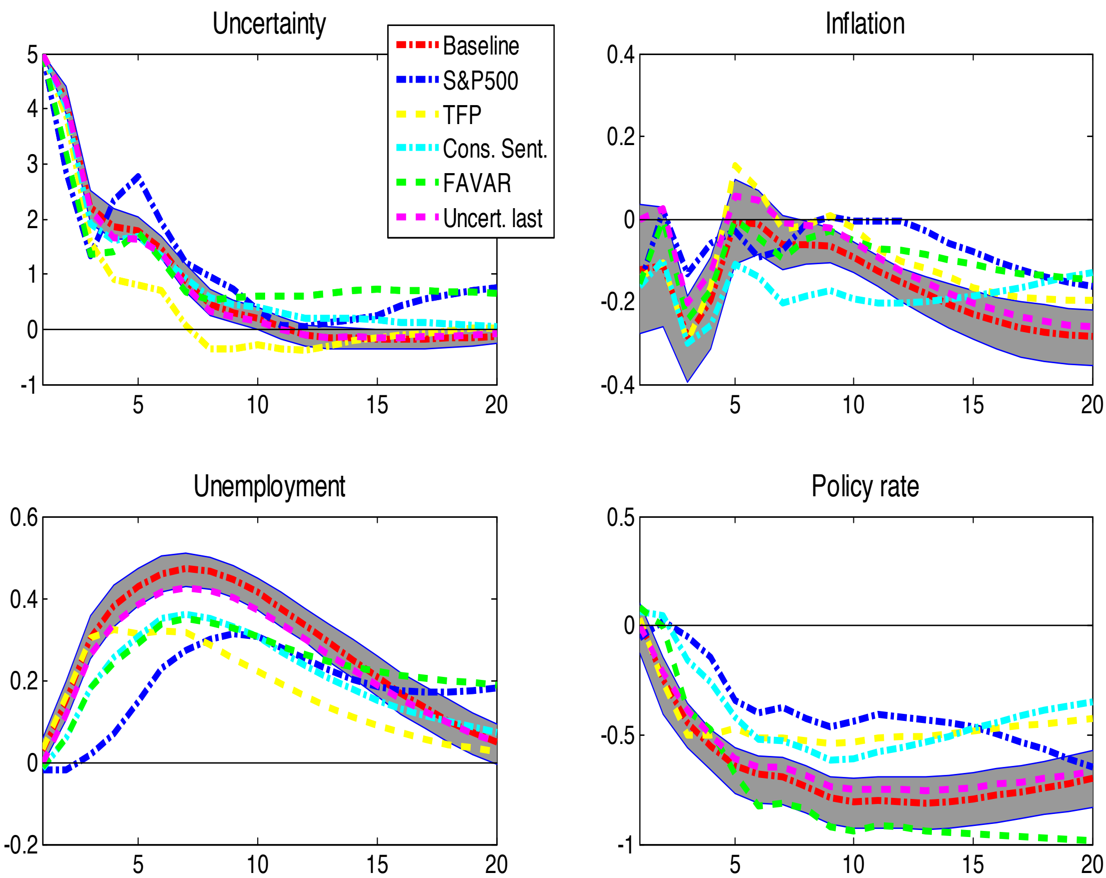

Figure 5: **Macroeconomic effects of uncertainty in recessions: Robustness checks**. Effects of a one standard deviation shock to VIX. Sample: 1962Q3-2012Q3. Dash-dotted red lines: Reactions under recessions computed with our non-linear framework. Baseline VAR with four variables (uncertainty, inflation, unemployment, policy rate). S&P500: quartely observations of the (cubically detrended) log of the S&P500 index placed on top of the baseline VAR. TFP: VAR with the linearly-detrended utilization adjusted-(log)series of TFP à la Fernald (2012) on top of the variables in the baseline vector. Cons. Sent.: VAR featuring the Consumer Sentiment from the Michigan Survey placed on top of the baseline VAR. FAVAR: VAR with a common factor extracted from 150 U.S. time series placed on top of the baseline VAR. Uncert. last: Uncertainty placed last in the otherwise baseline VAR. Gray areas: 90% confidence sets surrounding our baseline estimates. Shocks identified with a Cholesky-decomposition of the variance-covariance matrix of the reduced-form residuals.

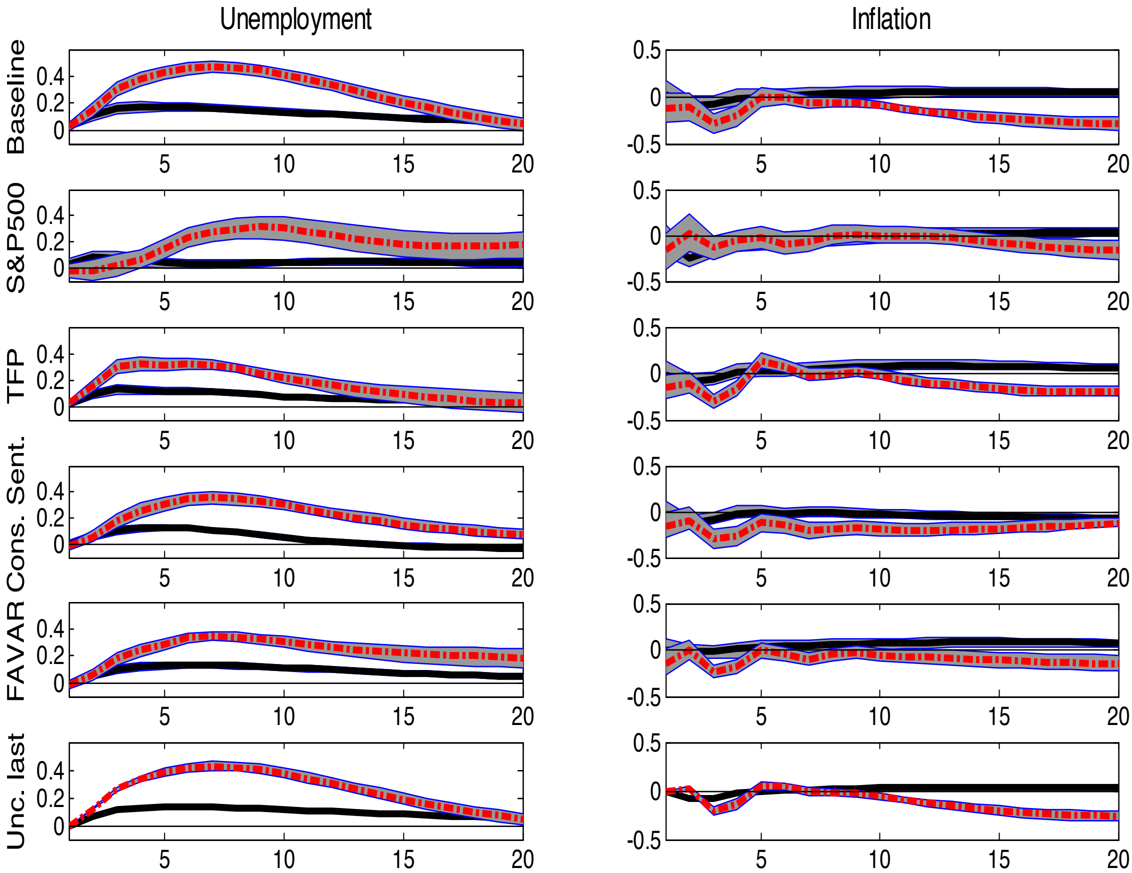

Figure 6: **Robustness checks: Omitted variables/alternative orderings**. Effects of a one standard deviation shock to VIX. Sample: 1962Q3-2012Q3. Solid black lines: Responses predicted by a linear VAR. Dash-dotted red lines: Reactions under recessions computed with our non-linear framework. Baseline VAR with four variables (uncertainty, inflation, unemployment, policy rate). S&P500: quartely observations of the (cubically detrended) log of the S&P500 index placed on top of the baseline VAR. TFP: VAR with the linearly-detrended utilization adjusted-(log)series of TFP à la Fernald (2012) on top of the variables in the baseline vector. Cons. Sent.: VAR featuring the Consumer Sentiment from the Michigan Survey placed on top of the baseline VAR. FAVAR: VAR with a common factor extracted from 150 U.S. time series placed on top of the baseline VAR. Uncert. last: Uncertainty placed last in the otherwise baseline VAR. Gray areas: 90% confidence sets surrounding our baseline estimates. Shocks identified with a Cholesky-decomposition of the variance-covariance matrix of the reduced-form residuals.

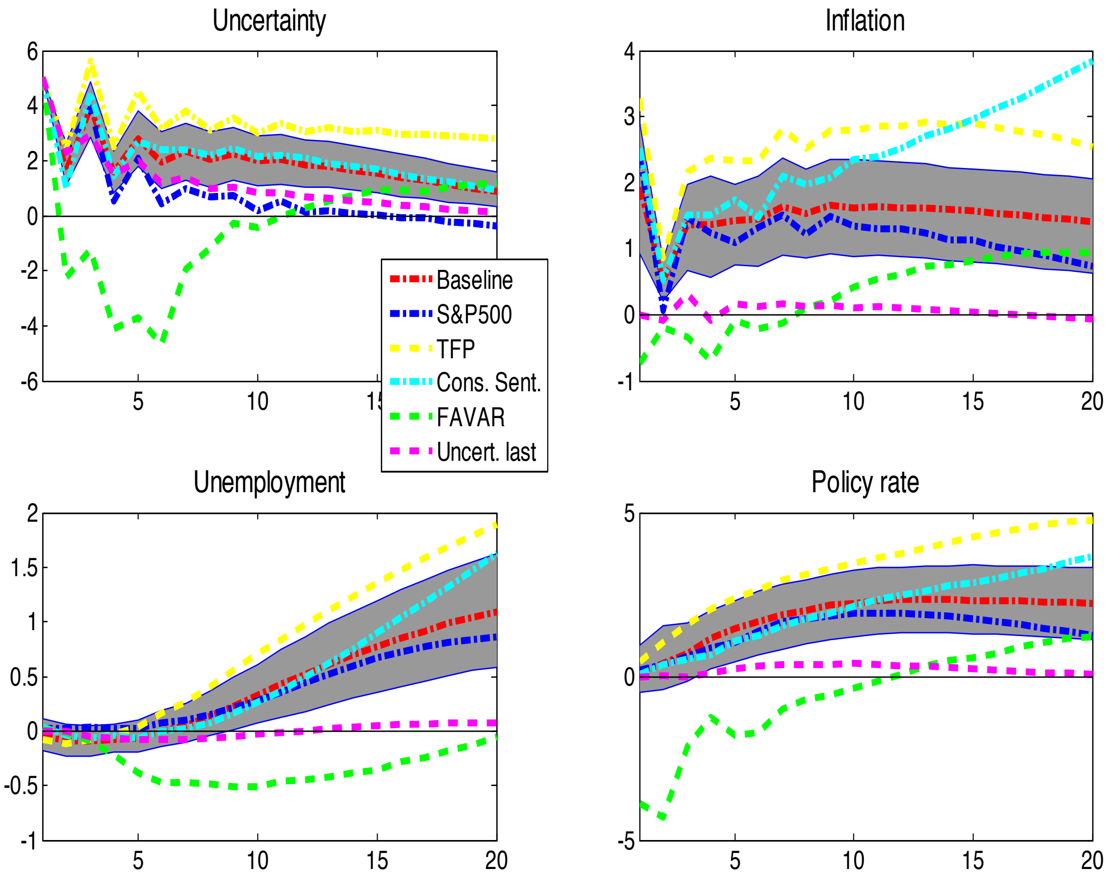

Figure 7: **Macroeconomic effects of uncertainty in non-recessionary periods: Robustness checks**. Effects of a one standard deviation shock to VIX. Sample: 1962Q3-2012Q3. Dash-dotted red lines: Reactions under recessions computed with our non-linear framework. Baseline VAR with four variables (uncertainty, inflation, unemployment, policy rate). S&P500: quartely observations of the (cubically detrended) log of the S&P500 index placed on top of the baseline VAR. TFP: VAR with the linearly-detrended utilization adjusted-(log)series of TFP à la Fernald (2012) on top of the variables in the baseline vector. Cons. Sent.: VAR featuring the Consumer Sentiment from the Michigan Survey placed on top of the baseline VAR. FAVAR: VAR with a common factor extracted from 150 U.S. time series placed on top of the baseline VAR. Uncert. last: Uncertainty placed last in the otherwise baseline VAR. Gray areas: 90% confidence sets surrounding our baseline estimates. Shocks identified with a Cholesky-decomposition of the variance-covariance matrix of the reduced-form residuals.

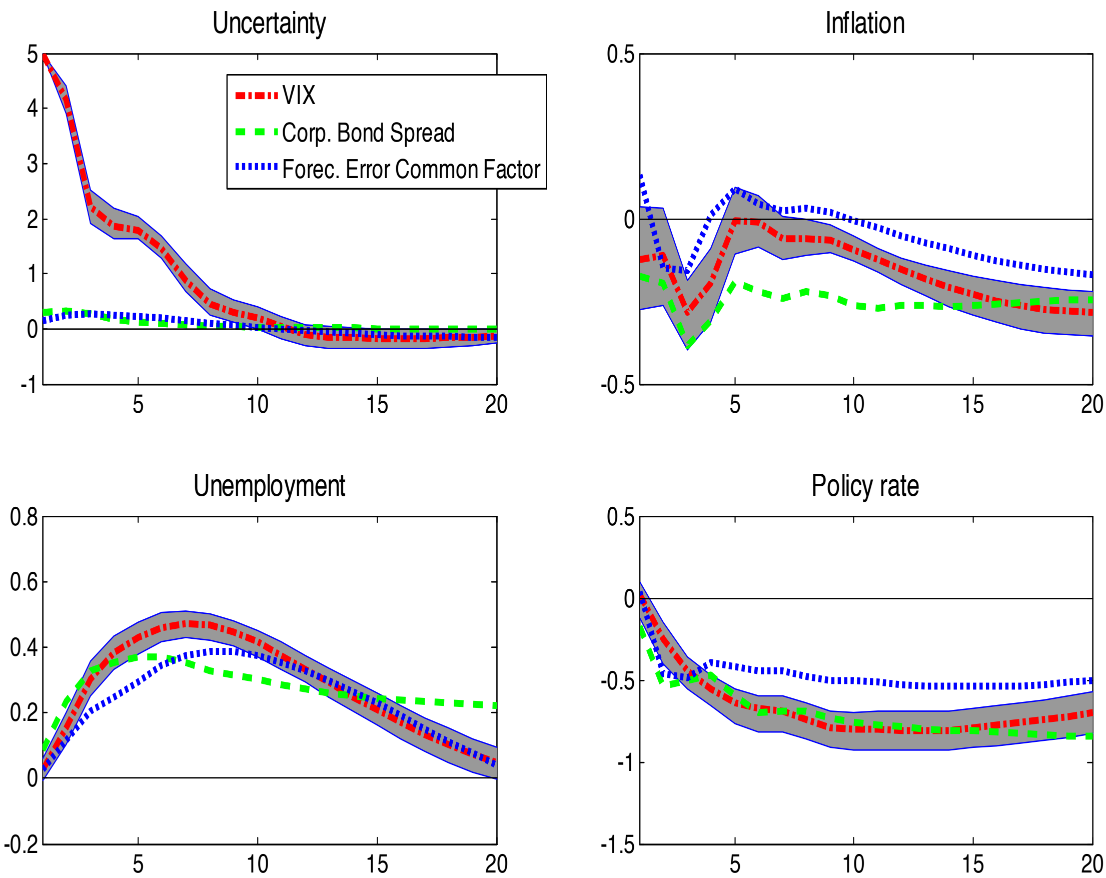

Figure 8: **Impact of uncertainty measures: Comparison.** Effects of a one standard deviation shock to each uncertainty indicator. Note: VIX and Corporate Bond Spread, sample: 1962Q3-2012Q3. Forec. Error Common Factor: Common factor of the one year-ahead forecast error variance computed as in Jurado, Ludvigson, and Ng (2013). Quarterly realizations computed as within-quarter averages of monthly estimates. Gray areas: 90% confidence sets surrounding our baseline estimates. Note: Sample of the Forec. Error Common Factor analysis: 1962Q3-2011Q4 (due to data availability).

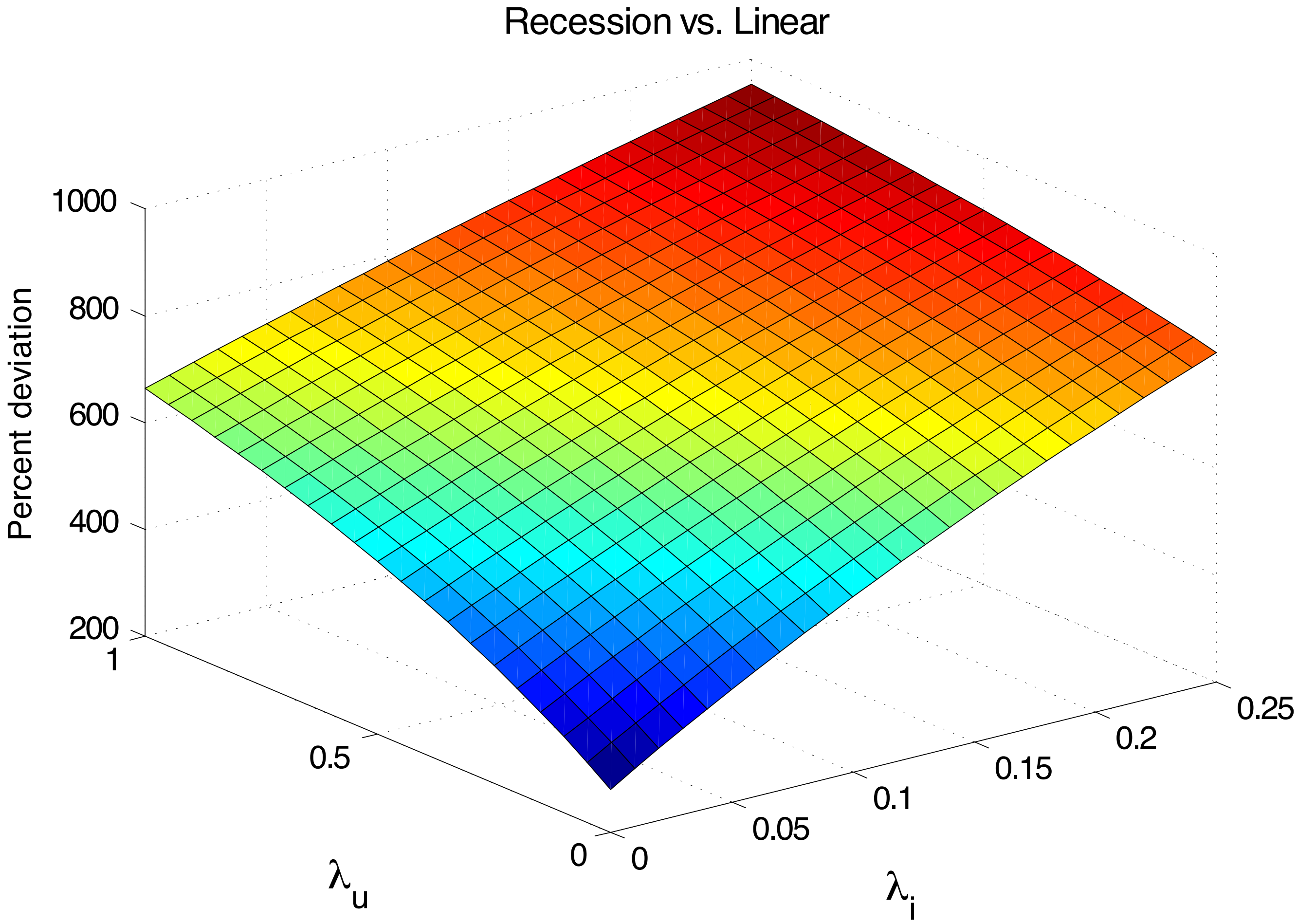

Figure 9: **Welfare loss, non-linear vs. linear VARs: Percent deviation.** Loss function: Quadratic loss function involving the variance of inflation, unemployment and the policy rate. Weights of unemployment and the policy rate on the x- and y-axes. Impulse response-driven losses computed on the basis of the first 12 horizons after the shock. Figure based on our baseline VAR.

Appendix of "Uncertainty Shocks and Unemployment Dynamics: An Analysis of Post-WWII U.S. Recessions" by Giovanni Caggiano, Efrem Castelnuovo, Nicolas Groshenny

This Appendix documents statistical evidence in favor of a non-linear relationship between unemployment and uncertainty. It also offers some details on the estimation of our non-linear VARs, as well as on the computation of the factors employed to perform our FAVAR estimations. Finally, it reports some extra-results, which have not been included in the paper for the sake of brevity.

Statistical evidence in favor of non-linearities

We begin our empirical analysis with a simple univariate autoregressive model for the unemployment rate, which we augment to take into account the possible non-linear role of uncertainty. The model is the following:

$$u_t = c + \sum_{i=1}^{k} \left(\beta_{u,i} u_{t-i} + \beta_{vix,i} vix_{t-i} + \beta_{u\_vix,i} u_{t-i} vix_{t-i} \right) + \varepsilon_t. \tag{1}$$

We estimate this model with U.S. quarterly data on unemployment and uncertainty (the latter being proxied by the VIX index) spanning the period 1962Q3-2012Q3 (a description of the data is provided later in this Section). The model is endowed with two lags for each regressor, and estimated by Ordinary-Least Squares. Our point estimates, along with our White heteroskedasticity-consistent standard errors, are displayed below:[1]

$$\begin{aligned} u_t \;=\; & \underset{(0.098)}{0.149} + \underset{(0.079)}{1.414} u_{t-1} - \underset{(0.073)}{0.457} u_{t-2} + \underset{(0.004)}{0.008} vix_{t-1} - \underset{(0.004)}{0.002} vix_{t-2} \\ & - \underset{(0.002)}{0.008} u_{t-1} vix_{t-1} + \underset{(0.002)}{0.006} u_{t-2} vix_{t-2} + \widehat{\varepsilon}_t. \end{aligned}$$

As shown by Luukkonen, Saikkonen, and Teräsvirta (1988), if the coefficients of the interaction terms $\beta_{u\_vix,1}$ and $\beta_{u\_vix,2}$ are non-zero, the assumption of linearity

[1] The absence of serial correlation of the estimated residual cannot be rejected by the Breusch-Godfrey Lagrange Multiplier test, which delivers a p-value associated to the asymptotic χ^2 distribution equal to 0.90 (with two lags of the residuals used in the regression conducted for testing purposes). Consequently, the results obtained with a Newey-West heteroskedasticity-consistent correction of the standard errors are virtually the same as those presented in the paper.

in the relationship between unemployment and uncertainty is rejected by the data (see also Tsay, 1986). The p-value of a F-test conducted under the null hypothesis $H_0 : \beta_{u\_vix,1} = \beta_{u\_vix,2} = 0$ equals 0.003, which is a clear rejection of the assumption of linearity.

To detect non-linear dynamics at a multivariate level, we apply the test proposed by Teräsvirta and Yang (2013). Their framework is particularly well suited for our analysis since it amounts to test the null hypothesis of linearity versus a specified nonlinear alternative, that of a (Logistic) Smooth Transition Vector AutoRegression with a single transition variable.

Consider the following $p-$dimensional 2-regime approximate logistic STVAR model:

$$\mathbf{X}_t = \mathbf{\Theta}_0' \mathbf{Y}_t + \mathbf{\Theta}_1' \mathbf{Y}_t z_t + \boldsymbol{\varepsilon}_t \tag{2}$$

where $\mathbf{X}_t = [vix_t, \pi_t, u_t, R_t]'$ is the $(p \times 1)$ vector of endogenous variables, where vix_t is the VIX index, π_t is inflation, u_t is the unemployment rate, R_t is a policy rate; $\mathbf{Y}_t = [\mathbf{X}_{t-1}| \ldots |\mathbf{X}_{t-k}|\boldsymbol{\alpha}]$ is the $((k \times p + q) \times 1)$ vector of exogenous variables (including endogenous variables lagged k times and a column vector of constants $\boldsymbol{\alpha}$), z_t is the transition variable, and $\mathbf{\Theta}_0$ and $\mathbf{\Theta}_1$ are matrices of parameters. In our case, the number of endogenous variables is $p = 4$, the number of exogenous variables is $q = 1$ and the number of lags is $k = 1$ (this is due to the 'curse of dimensionality', as indicated in Teräsvirta and Yang, 2012). Under the null hypothesis of linearity, $\mathbf{\Theta}_1 = \mathbf{0}$.

The Teräsvirta-Yang test for linearity versus the STVAR model can be performed as follows:

1. Estimate the restricted model ($\mathbf{\Theta}_1 = \mathbf{0}$) by regressing $\mathbf{X}_t$ on $\mathbf{Y}_t$. Collect the residuals $\tilde{\mathbf{E}}$ and the matrix residual sum of squares $\mathbf{RSS}_0 = \tilde{\mathbf{E}}'\tilde{\mathbf{E}}$.

2. Run an auxiliary regression of $\tilde{\mathbf{E}}$ on $(\mathbf{Y}_t, \mathbf{Z}_1)$ where $\mathbf{Z}_1 = [\mathbf{X}_t' z_t]$. Collect the residuals $\tilde{\mathbf{\Xi}}$ and compute the matrix residual sum of squares $\mathbf{RSS}_1 = \tilde{\mathbf{\Xi}}'\tilde{\mathbf{\Xi}}$.

3. Compute the test-statistic

$$\begin{aligned} LM &= T tr \left\{ \mathbf{RSS}_0^{-1} (\mathbf{RSS}_0 - \mathbf{RSS}_1) \right\} \\ &= T \left(p - tr \left\{ \mathbf{RSS}_0^{-1} \mathbf{RSS}_1 \right\} \right) \end{aligned}$$

   Under the null hypothesis, the test statistic is distributed as a χ^2 with $p\,(kp + q)$ degrees of freedom (in our case, 20 degrees of freedom). For our model, we get $LM = 34.52$, corresponding to a p-value of 0.0228. Hence, we reject the null hypothesis of linearity at conventional confidence levels.

Estimation of the non-linear VARs

Our model (3)-(6) is estimated via maximum likelihood.[2] The model's log-likelihood reads as follows:

$$\log L = const + \frac{1}{2}\sum_{t=1}^{T} \log|\boldsymbol{\Omega}_t| - \frac{1}{2}\sum_{t=1}^{T} \boldsymbol{u}_t'\boldsymbol{\Omega}_t^{-1}\boldsymbol{u}_t \tag{A1}$$

where the vector of residuals $\boldsymbol{u}_t = \boldsymbol{X}_t - (1 - F(z_{t-1}))\boldsymbol{\Pi}_{NR}\boldsymbol{X}_{t-1} - F(z_{t-1})\boldsymbol{\Pi}_R\boldsymbol{X}_{t-1}$. Our goal is to estimate the parameters $\boldsymbol{\Psi} = \{\gamma, \boldsymbol{\Omega}_R, \boldsymbol{\Omega}_{NR}, \boldsymbol{\Pi}_R(L), \boldsymbol{\Pi}_{NR}(L)\}$, where $\boldsymbol{\Pi}_j(L) = \begin{bmatrix} \boldsymbol{\Pi}_{j,1} & \ldots & \boldsymbol{\Pi}_{j,p} \end{bmatrix}$, $j \in \{R, NR\}$. The high-non linearity of the model and its many parameters render its estimation with standard optimization routines problematic. Following Auerbach and Gorodnichenko (2012), we employ the procedure described below.

Conditional on $\{\gamma, \boldsymbol{\Omega}_R, \boldsymbol{\Omega}_{NR}\}$, the model is linear in $\{\boldsymbol{\Pi}_R(L), \boldsymbol{\Pi}_{NR}(L)\}$. Then, for a given guess on $\{\gamma, \boldsymbol{\Omega}_R, \boldsymbol{\Omega}_{NR}\}$, the coefficients $\{\boldsymbol{\Pi}_R(L), \boldsymbol{\Pi}_{NR}(L)\}$ can be estimated by minimizing $\frac{1}{2}\sum_{t=1}^{T} \boldsymbol{u}_t'\boldsymbol{\Omega}_t^{-1}\boldsymbol{u}_t$. This can be seen by re-writing the regressors as follows. Let $\boldsymbol{W}_t = \begin{bmatrix} F(z_{t-1})\boldsymbol{X}_{t-1} & (1 - F(z_{t-1}))\boldsymbol{X}_{t-1} & \ldots & F(z_{t-1})\boldsymbol{X}_{t-p} & (1 - F(z_{t-1}))\boldsymbol{X}_{t-p} \end{bmatrix}$ be the extended vector of regressors, and $\boldsymbol{\Pi} = \begin{bmatrix} \boldsymbol{\Pi}_R(L) & \boldsymbol{\Pi}_{NR}(L) \end{bmatrix}$. Then, we can write $\boldsymbol{u}_t = \boldsymbol{X}_t - \boldsymbol{\Pi}\boldsymbol{W}_t'$. Consequently, the objective function becomes

$$\frac{1}{2}\sum_{t=1}^{T}(\boldsymbol{X}_t - \boldsymbol{\Pi}\boldsymbol{W}_t')'\boldsymbol{\Omega}_t^{-1}(\boldsymbol{X}_t - \boldsymbol{\Pi}\boldsymbol{W}_t').$$

It can be shown that the first order condition with respect to $\boldsymbol{\Pi}$ is

$$vec\boldsymbol{\Pi}' = \left(\sum_{t=1}^{T}\left[\boldsymbol{\Omega}_t^{-1} \otimes \boldsymbol{W}_t'\boldsymbol{W}_t\right]\right)^{-1} vec\left(\sum_{t=1}^{T}\boldsymbol{W}_t'\boldsymbol{X}_t\boldsymbol{\Omega}_t^{-1}\right). \tag{A2}$$

This procedure iterates over different sets of values for $\{\gamma, \boldsymbol{\Omega}_R, \boldsymbol{\Omega}_{NR}\}$. For each set of values, $\boldsymbol{\Pi}$ is obtained and the $logL$ (A1) computed.

Given that the model is highly non-linear in its parameters, several local optima might be present. Hence, it is recommended to try different starting values for $\{\gamma, \boldsymbol{\Omega}_R, \boldsymbol{\Omega}_{NR}\}$. To ensure positive definiteness of the matrices $\boldsymbol{\Omega}_R$ and $\boldsymbol{\Omega}_{NR}$, we focus on the alternative vector of parameters $\boldsymbol{\Psi} = \{\gamma, chol(\boldsymbol{\Omega}_R), chol(\boldsymbol{\Omega}_{NR}), \boldsymbol{\Pi}_R(L), \boldsymbol{\Pi}_{NR}(L)\}$, where $chol$ implements a Cholesky decomposition.

The construction of confidence intervals for the parameter estimates as well as the impulse responses is complicated by, once again, the non-linear structure of the problem. We compute them by appealing to a Markov Chain Monte Carlo (MCMC) algorithm

[2] This Section heavily draws on Auerbach and Gorodnichenko's (2012) "Appendix: Estimation Procedure".

developed by Chernozhukov and Hong (2003) (CH hereafter). This method delivers both a global optimum and densities for the parameter estimates. Hence, we are able to compute confidence intervals for the impulse responses.

CH estimation is implemented via a Metropolis-Hastings algorithm. Given a starting value $\boldsymbol{\Psi}^{(0)}$, the procedure constructs chains of length N of the parameters of our model following these steps:

Step 1. Draw a candidate vector of parameter values $\boldsymbol{\Theta}^{(n)} = \boldsymbol{\Psi}^{(n)} + \boldsymbol{\psi}^{(n)}$ for the chain's $n+1$ state, where $\boldsymbol{\Psi}^{(n)}$ is the current state and $\boldsymbol{\psi}^{(n)}$ is a vector of i.i.d. shocks drawn from $N(0, \boldsymbol{\Omega}_{\Psi})$, and $\boldsymbol{\Omega}_{\Psi}$ is a diagonal matrix.

Step 2. Set the $n+1$ state of the chain $\boldsymbol{\Psi}^{(n+1)} = \boldsymbol{\Theta}^{(n)}$ with probability $min\left\{1, L(\boldsymbol{\Theta}^{(n)})/L(\boldsymbol{\Psi}^{(n)})\right\}$, where $L(\boldsymbol{\Theta}^{(n)})$ is the value of the likelihood function conditional on the candidate vector of parameter values, and $L(\boldsymbol{\Psi}^{(n)})$ the value of the likelihood function conditional on the current state of the chain. Otherwise, set $\boldsymbol{\Psi}^{(n+1)} = \boldsymbol{\Psi}^{(n)}$.

The starting value $\boldsymbol{\Theta}^{(0)}$ is computed by working with a second-order Taylor approximation of the model (3)-(6), so that the model can be written as regressing $\boldsymbol{X}_t$ on lags of $\boldsymbol{X}_t$, $\boldsymbol{X}_t z_t$, and $\boldsymbol{X}_t z_t^2$. The residuals from this regression are employed to fit the expression for the reduced-form time-varying variance-covariance matrix of the VAR (see our paper) using maximum likelihood to estimate $\boldsymbol{\Omega}_R$ and $\boldsymbol{\Omega}_{NR}$. Conditional on these estimates and given a calibration for γ, we can construct $\boldsymbol{\Omega}_t$. Conditional on $\boldsymbol{\Omega}_t$, we can get starting values for $\boldsymbol{\Pi}_R(L)$ and $\boldsymbol{\Pi}_{NR}(L)$ via equation (A2).

The initial (diagonal matrix) $\boldsymbol{\Omega}_{\Psi}$ is calibrated to one percent of the parameter values. It is then adjusted "on the fly" for the first 20,000 draws to generate an acceptance rate close to 0.3, a typical choice for this kind of simulations (Canova (2007)). We employ $N = 50,000$ draws for our estimates, and retain the last 20% for inference.

As shown by CH, $\overline{\boldsymbol{\Psi}} = \frac{1}{N}\sum_{n=1}^{N} \boldsymbol{\Psi}^{(n)}$ is a consistent estimate of $\boldsymbol{\Psi}$ under standard regularity assumptions on maximum likelihood estimators. Moreover, the covariance matrix of $\boldsymbol{\Psi}$ is given by $\boldsymbol{V} = \frac{1}{N}\sum_{n=1}^{N}(\boldsymbol{\Psi}^{(n)} - \overline{\boldsymbol{\Psi}})^2 = var(\boldsymbol{\Psi}^{(n)})$, that is the variance of the estimates in the generated chain.

The chain of parameters $\left\{\boldsymbol{\Psi}^{(n)}\right\}_{n=1}^{N}$ is used to construct confidence intervals for the impulse responses. We draw 500 realizations (with replacement) from $\left\{\boldsymbol{\Psi}^{(n)}\right\}_{n=1}^{N}$. Per each draw, we calculate the impulse responses to the shock(s) of interest. The columns of $chol(\boldsymbol{\Omega}_R)$ and $chol(\boldsymbol{\Omega}_{NR})$ are identified up to a sign, hence the corresponding generated chains can change signs. While not being a problem as for estimation, this change in sign is an issue for the impulse responses. To address this issue, we construct the impulse responses by drawing $\{\mathbf{\Pi}_R(L), \mathbf{\Pi}_{NR}(L)\}$ directly from $\left\{\mathbf{\Psi}^{(n)}\right\}_{n=1}^{N}$, and the covariance matrix of residuals in regime j from $N(vec(\mathbf{\Omega}_j), \mathbf{\Sigma}_j)$, where

$$\mathbf{\Sigma}_j = 2[(\boldsymbol{D}_n'\boldsymbol{D}_n)^{-1}\boldsymbol{D}_n]\left\{var(vec(\mathbf{\Omega}_j)) \otimes var(vec(\mathbf{\Omega}_j))\right\}[(\boldsymbol{D}_n'\boldsymbol{D}_n)^{-1}\boldsymbol{D}_n]',$$

$\boldsymbol{D}_n$ is a duplication matrix, and $var(vec(\mathbf{\Omega}_j)$ is computed from $\left\{\mathbf{\Psi}^{(n)}\right\}_{n=1}^{N}$. The confidence bands are computed by selecting the relevant percentiles from the density of the generated impulse responses.

Computation of the factors for the FAVAR approach

We follow Stock and Watson (2012) to estimate the factors from a large unbalanced data set of US variables. Let $\boldsymbol{X}_t = (X_{1t}, \ldots, X_{nt})'$ denote a vector of n macroeconomic time series, with $t = 1, \ldots, T$. X_{it} is a single time series transformed to be stationary and to have mean zero. The dynamic factor model expresses each of the n time series as the sum of a common component driven by r unobserved factors $\boldsymbol{F}_t$ plus an idiosyncratic disturbance term e_{it}:

$$\mathbf{X}_t = \mathbf{\Lambda}\mathbf{F}_t + \mathbf{e}_t \tag{3}$$

where $\boldsymbol{e}_t = (e_{1t}, \ldots, e_{nt})'$ and $\mathbf{\Lambda}$ is the $n \times r$ matrix of factor loadings.

The factors are assumed to follow a linear and stationary vector autoregression:

$$\mathbf{\Phi}(L)\,\boldsymbol{F}_t = \boldsymbol{\eta}_t \tag{4}$$

where $\mathbf{\Phi}(L)$ is a $r \times r$ matrix of lag polynomials with the vector of r innovations $\boldsymbol{\eta}_t$. Stationarity implies that $\mathbf{\Phi}(L)$ can be inverted and $\boldsymbol{F}_t$ has the moving average representation:

$$\boldsymbol{F}_t = \mathbf{\Phi}(L)^{-1}\,\boldsymbol{\eta}_t. \tag{5}$$

With n large, under the assumption that there is a single-factor structure, simple cross-sectional averaging provides an estimate of $\boldsymbol{F}_t$ good enough to treat $\widehat{\boldsymbol{F}}_t$ as data in a regression without a generated regressor problem. With multiple factors, Stock and Watson (2002) show that a consistent estimate of $\boldsymbol{F}_t$ is obtained using principal components.

Our data set is standard in the recent literature on factor models (see Forni and Gambetti (2011) and Stock and Watson, 2012). It contains an unbalanced panel of 150 quarterly series, with starting date 1947Q1 and end date 2012Q3. The data are grouped into 12 categories: NIPA variables (31); industrial production (16); employment and unemployment (14); housing starts (6); inventories, orders and sales (12); prices (15); earnings and productivity (13); interest rates (10); money and credit (12); stock prices (5); exchange rates (7); and other (9). Earnings and productivity data include TFP-adjusted measures of capacity utilization introduced by Basu, Fernald, and Kimball (2006). The category labeled "other" includes expectations variables.

All series were transformed to be stationary with zero mean (see Table A1 for details). The factors were estimated using principal components as in Stock and Watson (2012). The assumption that the factors can be estimated with no breaks over the period 1947Q2-2012Q3 is motivated by the findings of Stock and Watson (2002), who show that the space spanned by the factors can be estimated consistently even if there is instability in $\mathbf{\Lambda}$.

References

Auerbach, A., and Y. Gorodnichenko (2012): "Measuring the Output Responses to Fiscal Policy," *American Economic Journal: Economic Policy*, 4(2), 1–27.

Basu, S., J. Fernald, and M. Kimball (2006): "Are Technology Improvements Contractionary?," *American Economic Review*, 96, 1418–1448.

Canova, F. (2007): Methods for Applied Macroeconomic Research, Princeton University Press, Princeton, New Jersey.

Chernozhukov, V., and H. Hong (2003): "An MCMC Approach to Classical Estimation," *Journal of Econometrics*, 115(2), 293–346.

Forni, M., and L. Gambetti (2011): "Testing for Sufficient Information in Structural VARs," CEPR Discussion Papers No. 8209.

Luukkonen, R., P. Saikkonen, and T. Teräsvirta (1988): "Testing linearity against smooth transition autoregressive models," *Biometrika*, 75, 491–499.

Stock, J. H., and M. W. Watson (2002): "Macroeconomic Forecasting Using Diffusion Indexes," *Journal of Business and Economic Statistics*, 20, 147–162.

——— (2012): "Disentangling the Channels of the 2007-2009 Recession," *Brookings Papers on Economic Activities*, forthcoming.

Tsay, R. (1986): "Nonlinearity tests for time series," *Biometrika*, 73, 461–466.

N	Series	Mnemonic	Tr.	Start	End
1	Real Gross Domestic Product, 1 Decimal	GDPC1	5	1947Q1	2012Q3
2	Real Gross National Product	GNPC96	5	1947Q1	2012Q3
3	Real National Income	NICUR/GDPDEF	5	1947Q1	2012Q3
4	Real Disposable Income	DPIC96	5	1947Q1	2012Q3
5	Real Personal Income	RPI	6	1959Q1	2012Q3
6	Nonfarm Business Sector: Output	OUTNFB	5	1947Q1	2012Q3
7	Real Final Sales of Domestic Product, 1 Decimal	FINSLC1	5	1947Q1	2012Q3
8	Real Private Fixed Investment, 1 Decimal	FPIC1	5	1995Q1	2012Q3
9	Real Private Residential Fixed Investment, 1 Decimal	PRFIC1	5	1995Q1	2012Q3
10	Real Private Nonresidential Fixed Investment, 1 Decimal	PNFIC1	5	1995Q1	2012Q3
11	Real Gross Private Domestic Investment, 1 Decimal	GPDIC1	5	1947Q1	2012Q3
12	Real Personal Consumption Expenditure	PCECC96	5	1947Q1	2012Q3
13	Real Personal Consumption Expenditure: Nondurable Goods	PCNDGC96	5	1995Q1	2012Q3
14	Real Personal Consumption Expenditure: Durable Goods	PCDGCC96	5	1995Q1	2012Q3
15	Real Personal Consumption Expenditure: Services	PCESVC96	5	1995Q1	2012Q3
16	Real Gross Private Saving	GPSAVE/GDPDEF	5	1947Q1	2012Q3
17	Real Federal Consumption Expenditures, Gross Investment, 1 Decimal	FGCEC1	5	1995Q1	2012Q3
18	Federal Goverment: Current Expenditures, Real	FGEXPND/GDPDEF	5	1947Q1	2012Q3
19	Federal Goverment: Current Receipts, Real	FGRECPT/GDPDEF	5	1947Q1	2012Q3
20	Net Federal Government Saving	FGDEF	2	1947Q1	2012Q3
21	Government Current Expenditures/GDP Deflator	GEXPND/GDPDEF	5	1947Q1	2012Q3
22	Government Current Receipts/GDP Deflator	GRECPT/GDPDEF	5	1947Q1	2012Q3
23	Government Real Expenditures minus Real Receipts	GDEF	2	1947Q1	2012Q3
24	Real Government Consumption Expenditures, Gross Investment, 1 Decimal	GCEC1	5	1947Q1	2012Q3
25	Real Change in Private Inventories, 1 Decimal	CBIC1	1	1947Q1	2012Q3
26	Real Exports of Goods and Services, 1 Decimal	EXPGSC1	5	1947Q1	2012Q3
27	Real Imports of Goods and Services, 1 Decimal	IMPGSC1	5	1947Q1	2012Q3
28	Corporate Profits After Tax, Real	CP/GDPDEF	5	1947Q1	2012Q3
29	Nonfinancial Corporate Business: Profits After Tax, Real	NFCPATAX/GDPDEF	5	1947Q1	2012Q3
30	Corporate Net Cash Flow, Real	CNCF/GDPDEF	5	1947Q1	2012Q3
31	Net Corporate Dividends, Real	DIVIDEND/GDPDEF	5	1947Q1	2012Q3
32	Industrial Production Index	INDPRO	5	1947Q1	2012Q3
33	Industrial Production: Business Equipment	IPBUSEQ	5	1947Q1	2012Q3
34	Industrial Production: Consumer Goods	IPCONGD	5	1947Q1	2012Q3
35	Industrial Production: Durable Consumer Goods	IPDCONGD	5	1947Q1	2012Q3
36	Industrial Production: Final Products (Market Group)	IPFINAL	5	1947Q1	2012Q3
37	Industrial Production: Materials	IPMAT	5	1947Q1	2012Q3
38	Industrial Production: Nondurable Consumer Goods	IPNCONGD	5	1947Q1	2012Q3
39	Capacity Utilization: Manufacturing	MCUMFN	4	1972Q1	2012Q3
40	Industrial Production: Manufacturing	IPMAN	5	1972Q1	2012Q3
41	Industrial Production: Durable Manufacturing	IPDMAN	5	1972Q1	2012Q3
42	Industrial Production: Mining	IPMINE	5	1972Q1	2012Q3
43	Industrial Production: Nondurable Manufacturing	IPNMAN	5	1972Q1	2012Q3
44	Industrial Production: Durable Materials	IPDMAT	5	1947Q1	2012Q3
45	Industrial Production: Electric and Gas Utilities	IPUTIL	5	1972Q1	2012Q3
46	ISM Manufacturing: PMI Composite Index	NAPM	1	1948Q1	2012Q3
47	ISM Manufacturing: Production Index	NAPMPI	1	1948Q1	2012Q3
48	Average Weekly Hours of Production and Nonsupervisory Employees: Manuf.	AWHMAN	1	1948Q1	2012Q3
49	Average Weekly Overtime Hours of Prod. and Nonsupervisory Employees: Manuf.	AWOTMAN	2	1948Q1	2012Q3
50	Civilian Labor Force Participation Rate	CIVPART	2	1948Q1	2012Q3

Table A1. Time series employed for the computation of the factors. Description of the Table in two pages.

N	Series	Mnemonic	Tr.	Start	End
51	Civilian Labor Force	CLF160V	5	1948Q1	2012Q3
52	Civilian Employment	CE160V	5	1948Q1	2012Q3
53	All Employees: Total Private Industries	USPRIV	5	1947Q1	2012Q3
54	All Employees: Goods-Producing Industries	USGOOD	5	1947Q1	2012Q3
55	All Employees: Service-Providing Industries	SRVPRD	5	1947Q1	2012Q3
56	Unemployed	UNEMPLOY	5	1948Q1	2012Q3
57	Average (Mean) Duration of Unemployment	UEMPMEAN	2	1948Q1	2012Q3
58	Civilian Unemployment Rate	UNRATE	2	1948Q1	2012Q3
59	Index of Help-Wanted Advertising in Newspapers	A0M046	1	1959Q1	2012Q3
60	HOANBS/CNP160V	HOANBS/CNP160V	4	1948Q1	2012Q3
61	Initial Claims	ICSA	5	1967Q3	2012Q3
62	Housing Starts: Total: New Privately Owned Units Started	HOUST	5	1959Q1	2012Q3
63	Housing Starts in Northeast Census Region	HOUSTNE	5	1959Q1	2012Q3
64	Housing Starts in Midwest Census Region	HOUSTMW	5	1959Q1	2012Q3
65	Housing Starts in South Census Region	HOUSTS	5	1959Q1	2012Q3
66	Housing Starts in West Census Region	HOUSTW	5	1959Q1	2012Q3
67	New Private Housing Units Authorized by Building Permits	PERMIT	5	1960Q1	2012Q3
68	US Manufacturers New Orders for Non Defense Capital Goods	USNOIDN.D	5	1959Q2	2012Q3
69	US New Orders of Consumer Goods and Materials	USCNORCGD	5	1959Q2	2012Q3
70	US ISM Manufacturers Survey: New Orders Index SADJ	USNAPMNO	1	1950Q2	2012Q3
71	Retail Sales: Total (Excluding Food Services)	RSXFS	5	1992Q1	2012Q3
72	Value of Manufacturers' Total Inventories for All Manufacturing Industries	UMTMTI	5	1992Q1	2012Q3
73	Value of Manufacturers' Total Inventories for Durable Goods	AMDMTI	5	1992Q1	2012Q3
74	Value of Manufacturers' Total Inventories for Nondurable Goods Industries	AMNMTI	5	1992Q1	2012Q3
75	ISM Manufacturing: Inventories Index	NAPMII	1	1948Q1	2012Q3
76	ISM Manufacturing: New Orders Index	NAPMNOI	1	1948Q1	2012Q3
77	Value of Manufacturers' New Orders for Cons. Goods: Cons. Dur. Goods Ind.s	ACDGNO	5	1992Q1	2012Q3
78	Manuf.s' New Orders: Durable Goods	DGORDER	5	1992Q1	2012Q3
79	Value of Manuf.s' New Orders for Dur. Goods Ind.: Transp. Equipment	ANAPNO	5	1992Q1	2012Q3
80	Gross Domestic Product: Chain-type Price Index	GDPCTPI	5	1947Q1	2012Q3
81	Gross National Product: Chain-type Price Index	GNPCTPI	5	1947Q1	2012Q3
82	Gross Domestic Product: Implicit Price Deflator	GDPDEF	5	1947Q1	2012Q3
83	Gross National Product: Implicit Price Deflator	GNPDEF	5	1947Q1	2012Q3
84	Consumer Price Index for All Urban Consumers: All Items	CPIAUCSL	6	1947Q1	2012Q3
85	Consumer Price Index for All Urban Consumers: All Items Less Food	CPIULFSL	6	1947Q1	2012Q3
86	Consumer Price Index for All Urban Consumers: All Items Less Energy	CPILEGSL	6	1957Q1	2012Q3
87	Consumer Price Index for All Urban Consumers: All Items Less Food & Energy	CPILFESL	6	1957Q1	2012Q3
88	Consumer Price Index for All Urban Consumers: Energy	CPIENGSL	6	1947Q1	2012Q3
89	Consumer Price Index for All Urban Consumers: Food	CPIUFDSL	6	1947Q1	2012Q3
90	Producer Price Index: Finished Goods: Capital Equipment	PPICPE	6	1947Q1	2012Q3
91	Producer Price Index: Crude Materials for Further Processing	PPICRM	6	1947Q1	2012Q3
92	Producer Price Index: Finished Consumer Goods	PPIFCG	6	1947Q1	2012Q3
93	Producer Price Index: Finished Goods	PPIFGS	6	1947Q1	2012Q3
94	Spot Oil Price: West Texas Intermediate	OILPRICE	6	1947Q1	2012Q3
95	Nonfarm Business Sector: Hours of All Persons	HOANBS	5	1947Q1	2012Q3
96	Nonfarm Business Secotr: Output Per Hour of All Persons	OPHNFB	5	1947Q1	2012Q3
97	Nonfarm Business Sector: Unit Nonlabor Payments	UNLPNBS	5	1947Q1	2012Q3
98	Nonfarm Business Sector: Unit Labor Cost	ULCNFB	5	1947Q1	2012Q3
99	Compensation of Employees: Wages and Salary Accruals, Real	WASCUR/CPI	5	1947Q1	2012Q3
100	Nonfarm Business Sector: Compensation Per Hour	COMPNFB	5	1947Q1	2012Q3

Table A1 (continued). Time series employed for the computation of the factors. Description of the Table in the following page.

N	Series	Mnemonic	Tr.	Start	End
101	Nonfarm Business Sector: Real Compensation Per Hour	COMPRNFB	5	1947Q1	2012Q3
102	Growth in utilization-adjusted TFP	dtfp_util	1	1947Q2	2012Q3
103	Growth in business sector TFP	dtfp	1	1947Q2	2012Q3
104	Utilization in producing investment	du_invest	1	1947Q2	2012Q3
105	Utilization in producing non-investment business output	du_consumption	1	1947Q2	2012Q3
106	Utilization-adjusted TFP in producing equipment and consumer durables	dtfp_I_util	1	1947Q2	2012Q3
107	Utilization-adjusted TFP in producing non-equipment output	dtfp_C_util	1	1947Q2	2012Q3
108	Effective Federal Funds Rate	FEDFUNDS	2	1954Q3	2012Q3
109	3-Month Treasury Bill: Secondary Market Rate	TB3MS	2	1947Q1	2012Q3
110	1-Year Treasury Constant Maturity Rate	GS1	2	1953Q2	2012Q3
111	10-Year Treasury Constant Maturity Rate	GS10	2	1953Q2	2012Q3
112	Moody's Seasoned Aaa Corporate Bond Yield	AAA	2	1947Q1	2012Q3
113	Moody's Seasoned Baa Corporate Bond Yield	BAA	2	1947Q1	2012Q3
114	Bank Prime Loan Rate	MPRIME	2	1949Q1	2012Q3
115	GS10-FEDFUNDS Spread	GS10-FEDFUNDS	1	1954Q3	2012Q3
116	GS1-FEDFUNDS Spread	GS1-FEDFUNDS	1	1954Q3	2012Q3
117	BAA-FEDFUNDS Spread	BAA-FEDFUNDS	1	1954Q3	2012Q3
118	Non-Borrowed Reserves of Depository Institutions	BOGNONBR	5	1959Q1	2012Q3
119	Board of Gov. Total Reserves, Adjusted for Changes in Reserve Requirements	TRARR	5	1959Q1	2012Q3
120	Board of Gov. Monetary Base, Adjusted for Changes in Reserve Requirements	BOGAMBSL	5	1959Q1	2012Q3
121	M1 Money Stock	M1SL	5	1959Q1	2012Q3
122	M2 Less Small Time Deposits	M2MSL	5	1959Q1	2012Q3
123	M2 Money Stock	M2SL	5	1959Q1	2012Q3
124	Commercial and Industrial Loans at All Commercial Banks	BUSLOANS	5	1947Q1	2012Q3
125	Consumer Loans at All Commercial Banks	CONSUMER	5	1947Q1	2012Q3
126	Bank Credit at All Commercial Banks	LOANINV	5	1947Q1	2012Q3
127	Real Estate Loans at All Commercial Banks	REALLN	5	1947Q1	2012Q3
128	Total Consumer Credit Owned and Securitized, Outstanding	TOTALSL	5	1947Q1	2012Q3
129	St. Louis Adjusted Monetary Base	AMBSL (CHNG)	5	1947Q1	2012Q3
130	US Dow Jones Industrials Share Price Index (EP)	USSHRPRCF	5	1950Q2	2012Q3
131	US Standard & Poor's Index of 500 Common Stocks	US500STK	5	1950Q2	2012Q3
132	US Share Price Index NADJ	USI62...F	5	1957Q2	2012Q3
133	Dow Jones/GDP Deflator	DOW Jones/GDPDEF	5	1950Q2	2012Q3
134	S&P/GDP Deflator	S&P/GDPDEF	5	1950Q2	2012Q3
135	Trade Weighted U.S. Dollar Index: Major Currencies	TWEXMMTH	2	1973Q1	2012Q3
136	Euro/U.S. Foreign Exchange Rate	EXUSEU(-1)	5	1999Q1	2012Q3
137	Germany/U.S. Foreign Exchange Rate	EXGEUS	5	1971Q1	2001Q4
138	Switzerland/U.S. Foreign Exchange Rate	EXSZUS	5	1971Q1	2012Q3
139	Japan/U.S. Foreign Exchange Rate	EXJPUS	5	1971Q1	2012Q3
140	U.K./U.S. Foreign Exchange Rate	EXUSUK(-1)	5	1971Q1	2012Q3
141	Canada/U.S. Foreign Exchange Rate	EXCAUS	5	1971Q1	2012Q3
142	US The Conference Board Leading Economic Indicators Index SADJ	USCYLEADQ	5	1959Q1	2012Q3
143	US Economic Cycle Research Institute Weekly Leading Index	USECRIWLH	5	1950Q2	2012Q3
144	University of Michigan Consumer Sentiment: Personal Finances, Current	USUMPFNCH	2	1978Q1	2012Q3
145	University of Michigan Consumer Sentiment: Personal Finances, Expected	USUMPFNEH	2	1978Q1	2012Q3
146	University of Michigan Consumer Sentiment: Economic Outlook, 12 Months	USUMECO1H	2	1978Q1	2012Q3
147	University of Michigan Consumer Sentiment: Economic Outlook, 5 Years	USUMECO5H	2	1978Q1	2012Q3
148	University of Michigan Consumer Sentiment: Buying Conditions, Durables	USUMBUYDH	2	1978Q1	2012Q3
149	University of Michigan Consumer Sentiment Index	USUMCONSH	2	1991Q1	2012Q3
150	University of Michigan Consumer Sentiment - Current Conditions	USUMCNSUR	2	1991Q1	2012Q3

Table A1 (continued). **Time series employed for the computation of the factors**. Classification of the series: 1-31: "NIPA"; 32-47: "Industrial Production"; 48-61: "Employment and Unemployment"; 62-67: "Housing Starts"; 68-79: "Inventories", "Orders and Sales"; 80-94: "Prices"; 95-107: "Earnings and Productivity"; 108-117: "Interest Rates"; 118-129: "Money and Credit"; 130-134: "Stock Prices"; 135-141: "Exchange Rates"; 142-150: "Others". The column labeled "Tr." indicates the transformation applied to the series (1 = level, 2 = first difference, 3 = logarithm, 4 = second difference, 5 = first difference of logarithm, 6 = second difference of logarithm). Data source: Federal Reserve Bank of St. Louis' website.

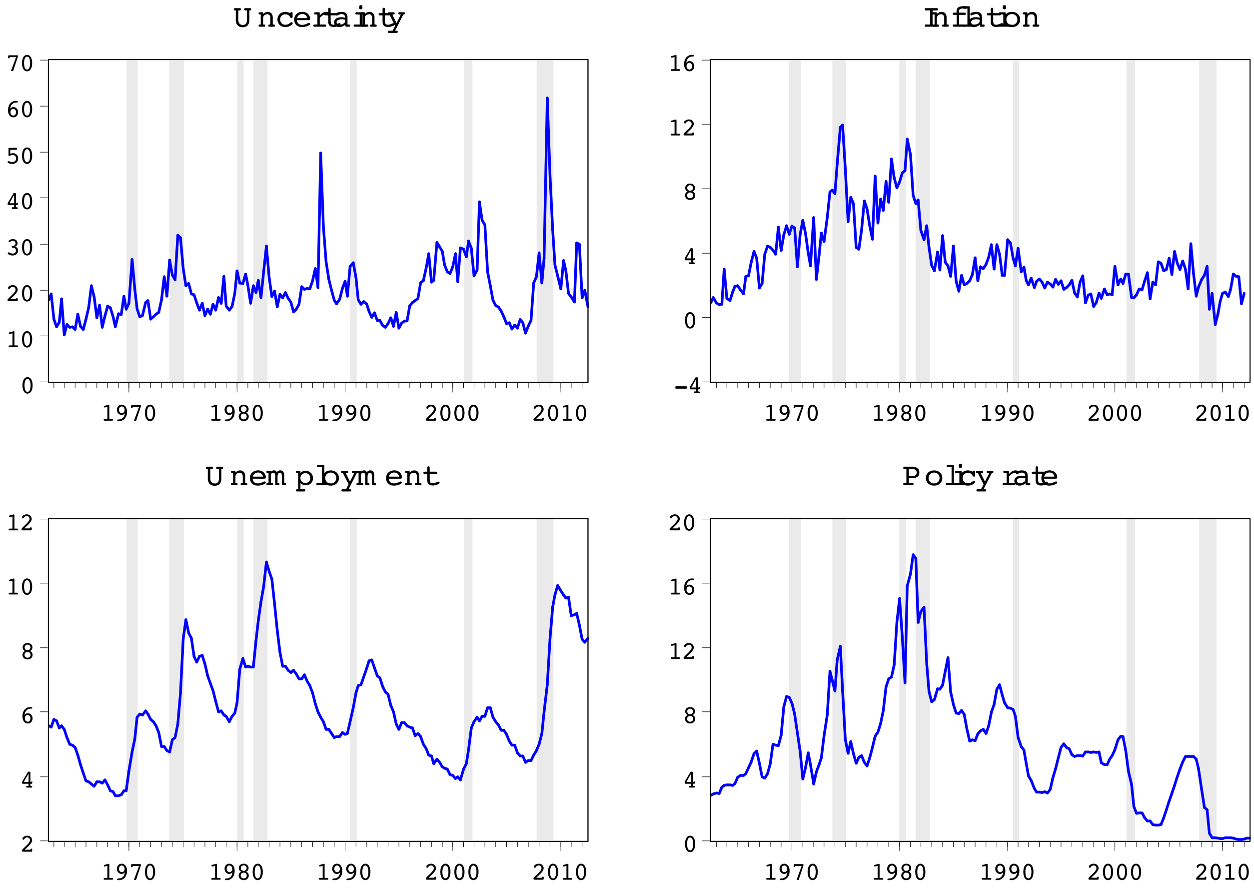

Figure A1 - Macroeconomic variables. Sample: 1962Q3-2012Q3. Uncertainty measured with the VIX as in Bloom (2009). Inflation measured as the annualized quarter-on-quarter growth rate of the implicit GDP deflator. Unemployment is the Civilian Unemployment rate. Policy rate is the Federal Funds Rate.

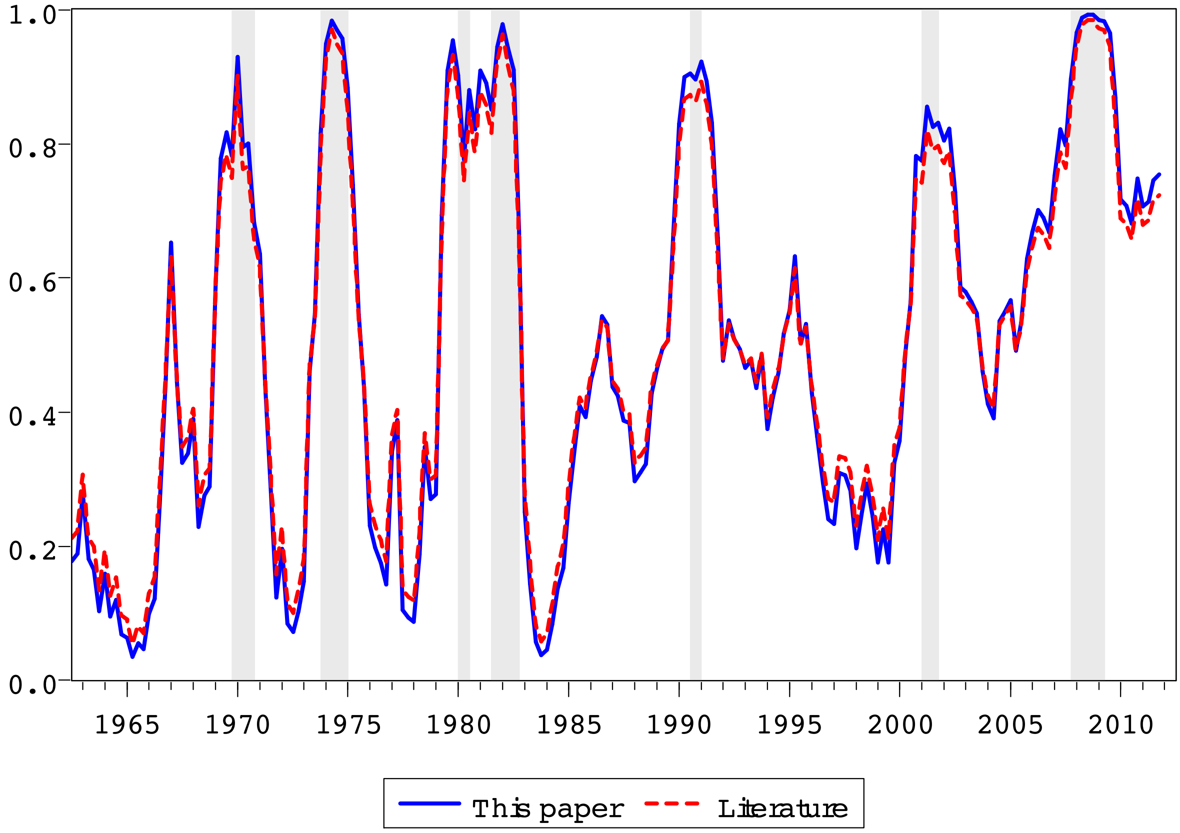

Figure 1:

Figure A2 - Probability of being in a recessionary phase. Blue solid line: Transition function F(z) as in this paper. Red dotted line: Transition function F(z) as in Auerbach and Gorodnichenko (2012) and Bauchmann and Sims (2012). Shaded columns: NBER recessions.