Uncertainty shocks and unemployment dynamics in U.S. recessions

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1. Introduction

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. Increasing attention has recently been paid to the role played by uncertainty. As stated by John Williams, 1 “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.”

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 (for a comprehensive survey, see Bloom et al., 2014). Part of the literature has studied the impact of uncertainty shocks with Dynamic Stochastic General Equilibrium models. 2 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 et al. (2013), Mumtaz and Theodoridis (2012), Baker et al. (2013), Gilchrist et al. (2013), Leduc and Liu (2013), Colombo (2013), Mumtaz and Surico (2013), and Nodari (2014). 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 et al., 2002; Morley and Piger, 2012; Morley et al., 2013), 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 et al., 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 isolate the impact of uncertainty shocks during recessions by modeling U.S. quarterly data on uncertainty, unemployment, and other standard macroeconomic variables with Smooth Transition Vector AutoRegressions (STVARs). 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, the predictions of the non-linear STVAR models conditional on recessions are then contrasted with those produced with standard linear VARs.

Our main results are the following. First, the impact of uncertainty shocks on unemployment is shown to be 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 0.14 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 0.36 percentage points four quarters after the shock, and 0.41 two years after the shock. Evidence of non-linear dynamics is also found for the policy rate and inflation. The asymmetry result holds not only for unemployment, but also for a number of alternative real activity indicators, including hours, output, investment, durable and nondurable consumption. Second, 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 a different data-frequency, a number of additional variables in our VARs, different identification schemes, different empirical proxies for uncertainty, and a shorter sample omitting the zero-lower bound, 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.

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 et al. (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 et al. (2013) 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) 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 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

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1 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). An investigation dealing with instabilities via a time-varying VAR approach is proposed by Benati (2013). A related approach is that by Enders and Jones (2013), who estimate Logistic Smooth Transition Autoregressive Models for a number of macroeconomic indicators. They isolate different effects of uncertainty shocks in the presence of “high” vs. “low” uncertainty. Differently, this paper focuses on the effects of uncertainty shocks during recessions (i.e., phases of “low” economic growth) and contrast such effects to what is typically found with standard linear VARs. In doing so, we employ a multivariate framework to model the systematic interaction among policy-relevant macroeconomic indicators such as inflation, unemployment, and a short-term interest rate. This enables us to control for spurious evidence of non-linearity possibly arising when omitting to model systematic interactions among structurally related variables.

2 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 (2002) 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.
increase in the unemployment rate. In the 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. A similar conclusion is reached by Basu and Bundick (2012), who show that sticky prices are important to generate a
contraction in output and its components after an exogenous increase in uncertainty. Our empirical findings support the
conclusions by these two latter papers, 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, our Smooth-Transition VAR model is presented. Second, the reasons behind our
focus on U.S. recessions are discussed.

2.1. Data and methodology

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

Formally, our STVAR model reads as follows:

\[
X_t = F(z_{t-1})\Pi_R(l)X_t + (1 - F(z_{t-1}))\Pi_{NR}(l)X_t + \epsilon_t, \\
\epsilon_t \sim N(0, \Omega_t), \\
\Omega_t = F(z_{t-1})\Omega_R + (1 - F(z_{t-1}))\Omega_{NR}, \\
F(z_t) = \exp(-\gamma z_t)/(1 + \exp(-\gamma z_t)), \quad \gamma > 0, \quad z_t \sim N(0, 1).
\]

where \(X_t\) 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 \(\gamma\), \(z_t\) is a transition indicator, \(\Pi_R\) and \(\Pi_{NR}\) are the VAR
coefficients capturing the dynamics of the system during recessions and non-recessionary phases, respectively, \(\epsilon_t\) is the
vector of reduced-form residuals having zero-mean and whose time-varying, state-contingent variance–covariance matrix
is \(\Omega_t\), and \(\Omega_R\) and \(\Omega_{NR}\) 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. The transition from a regime to another is regulated by the smoothness
parameter \(\gamma\). Large values of this parameter imply abrupt switches from a regime to another. Viceversa, moderate values of \(\gamma\)
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.

Our baseline analysis hinges upon the vector \(X_t = [\text{vix}_t, \pi_t, u_t, R_t]^\prime\), where \(\text{vix}_t\) stands for the VIX index, our proxy for
uncertainty, \(\pi_t\) 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 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), pre-1986 monthly returns volatilities are
computed 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
dunds’ 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.
The presence of non-linearities in the unemployment–uncertainty relationship is verified by running two tests. The first is based on a regression of unemployment rate on its own lags, uncertainty, and interaction terms between these two variables as regressors. As shown by Luukkonen et al. (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, the test proposed by Teräsvirta and Yang (2013) is then performed. Their framework is particularly suited for our analysis since it amounts to test the null hypothesis of linearity vs. a specified non-linear 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.5

The identification of exogenous variations of the uncertainty index is achieved via the widely adopted Cholesky-assumption. Given the ordering of the variables in X_t, this implies that one-impact macroeconomic effects by our identified uncertainty shocks are allowed. While being a common assumption in the literature, it must be noted that demand and supply shocks influencing the equilibrium values of our macroeconomic indicators may also influence uncertainty within a quarter. Hence, no recursive ordering is probably right in this context. Moreover, ordering the VIX first in our vector attributes all the one-step-ahead forecast error in the VIX to uncertainty shocks. Consequently, our results should be interpreted as providing an upper bound on the effects of uncertainty shocks.6 Importantly, our results are robust to the employment of monthly data, which make the recursive identifying restriction more plausible (see Caggiano et al., 2013).

A key role is played by the transition variable z_t. Following Auerbach and Gorodnichenko (2012), Bachmann and Sims (2012), and Berger and Vavra (2014), a standardized moving average involving seven realizations of the quarter-on-quarter real GDP growth rate is employed. The transition variable z_t is standardized to render our calibration of the slope parameter γ comparable to the ones employed in the literature. Auerbach and Gorodnichenko (2012) suggest to fix γ to ease the estimation of the remaining parameters of highly non-linear STVARs like ours. The smoothness parameter γ is calibrated by referring to the duration of recessions in the U.S. according to the NBER business cycle dates (17% of the time in our sample according to the dating proposed by the NBER). Then, “recessions” are defined as periods in which \( F(z_t) \geq 0.83 \), and γ is calibrated such that Pr(\( F(z_t) \geq 0.83 \)) ≈ 0.17. This metric implies a calibration γ ≈ 1.75, which is quite close to the 1.5 value employed by Auerbach and Gorodnichenko (2012), Bachmann and Sims (2012), and Berger and Vavra (2014).7

The transition function \( F(z_t) \) is shown in Fig. 1. 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 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.

Our (linear/non-linear) VAR features three lags. This choice is justified by the Akaike criterion 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 its high non-linearity, the model is estimated by the Monte-Carlo Markov-Chain simulation method proposed by Chernozhukov and Hong (2003).8 Notice that the indicator variable z_t is not embedded in our vector of modeled variables X_t. As discussed in Koop et al. (1996), absent any feedback from the endogenous variables to z_t, the impulse responses to an uncertainty shock can be computed by assuming regime-specific linear VARs. In other words, the macroeconomic reactions to uncertainty shocks are computed by assuming to start in a recession and to remain in such a state, i.e., the probability to switch to a non-recessory phase is set to zero. This choice is justified by our interest to focus on the short-run dynamics of the U.S. economic system. Moreover, it 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, the estimated uncertainty shocks (conditional on our linear VAR) are regressed on a constant and three lags of the transition variable. The p-value associated to the F-test on the predictive power of the transition variable as for future uncertainty shocks reads 0.10. The reason behind this result is the presence of the unemployment rate in our VAR. This hypothesis is corroborated by estimating uncertainty shocks with a trivariate VAR featuring uncertainty, inflation, and the federal funds rate only. When regressing such ‘shocks’ obtained with this model 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. Further considerations on the computation of our impulse responses are proposed in our Robustness checks section.

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 $F(z)$. 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). Fig. 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 et al. (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 et al. (2013); and the Economic Policy Uncertainty index developed by Baker et al. (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 conjecture is offered by a recent work by Jurado et al. (2013), who carefully estimate 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 (1973–1974, 1981–1982, 2007–2009). More generally, they find macro-uncertainty to be higher in recessions than in non-recessions years. Finally, 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), Galvao (2002), and Morley et al. (2013). 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.

3. Results

Fig. 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 the VAR.9 Unemployment increases significantly and persistently, and follows a hump-shaped path before going back to its steady-state value. The reaction of inflation is negative, though it is hardly significant. The policy rate decreases significantly after the shock for a limited number of quarters, following a pattern consistent with a flexible inflation targeting strategy by the Federal Reserve. These results are in line with those obtained by Basu and Bundick (2012) and 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, to some extent, lower inflation.

A quantitatively very different picture emerges when non-linearities are admitted to play a role in this system. Fig. 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

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9 Caggiano et al. (2013) show that our results are robust to using alternative indicators of uncertainty like the macro-uncertainty factor computed by Jurado et al. (2013) as well as the Corporate Bond Spread considered by Bachmann et al. (2013).
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 0.14 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 0.36 percentage points four quarters after the shock, and 0.41 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 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 a flexible inflation targeting strategy. Similar to inflation and unemployment, the federal funds’ rate is estimated to be more sensitive to uncertainty shocks during recessions.

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 switch from the recessionary phase. One should therefore interpret the estimated responses under recessions as an 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.

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 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 under recessions 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. Hence, our results lend support to the analysis proposed by Basu and Bundick (2012), who show that the introduction of price stickiness in an otherwise standard RBC framework enables their model to replicate the recessionary and deflationary effects of an exogenous increase in uncertainty.

Fig. 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, and policy rate). Gray areas: 68% bootstrapped confidence bands. Shocks identified with a Cholesky-decomposition of the variance–covariance matrix of the reduced-form residuals. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)
4. Robustness checks

Our exercises suggest that uncertainty shocks are important for the U.S. unemployment dynamics. However, some robustness checks are in order.

4.1. ZLB

First, our results may be due to the Zero-Lower Bound (ZLB) affecting conventional monetary policy moves concerning the nominal interest rate. The Federal Reserve has hit the zero lower bound in December 2008. Since then, it has maintained the fed funds rate at historically low levels. A number of studies have argued that the impact of uncertainty shocks might be substantially more pronounced when the ZLB binds (Basu and Bundick, 2012; Johannsen, 2013). The model is then estimated by considering the sample 1962Q3–2008Q3, which excludes the years of the Great Recession affected by the presence of the ZLB. Fig. 5 shows our results. In the absence of ZLB, the response of unemployment is weaker and shorter-lived. Its peak response under recessions is equal to 0.30 percentage points and occurs five quarters after the shock vs. a peak equal to 0.42 percentage points occurring six quarters after the shock in the baseline scenario. Consistently, the maximum (in absolute value) reaction of the policy rate in recessions is estimated to be about 0.71 percentage points when the observations about the ZLB are included in the sample vs. about 0.92 percentage points when they are excluded. Interestingly, in the absence of the ZLB, the path of the unemployment rate suggests a possible “overshoot” some 10 quarters after the shock. This evidence points to the possibility of a “wait-and-see” type of behavior by firms in the presence of an increase in uncertainty (Bloom, 2009). Our results suggest that the presence of the ZLB may indeed magnify the macroeconomic effects of uncertainty. Hence, our findings lend support to the theoretical predictions put forth by Basu and Bundick (2012) and Johanssen (2013) on the stronger macroeconomic effects of uncertainty shocks in the presence of the ZLB.

4.2. Alternative indicators of macroeconomic “activity”

Our analysis focuses on the unemployment rate. While being of clear interest from a policymaking standpoint, this variable is affected by measurement issues due to time-varying labor market participation. Moreover, it has some very low-frequency movements. Several experiments with a variety of alternative indicators of macroeconomic “activity” are

![Fig. 5. Macroeconomic effects of uncertainty in recessions: pre zero-lower bound sample. Effects of a one standard deviation shock to VIX. Sample: 1962Q3–2008Q3. 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, and policy rate). Gray areas: 68% bootstrapped confidence bands. Shocks identified with a Cholesky-decomposition of the variance–covariance matrix of the reduced-form residuals. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)](image-url)
conducted. In particular, we rotate series of hours, output, investment, durable consumption, and non-durable consumption in one at a time and estimate four-variate VARs with these alternative series

$$X_t = \left[ \text{activity}_t, \pi_t, \text{activity}_t, R_t \right]^\top.$$  

Fig. 6 displays the responses of our alternative measures of real activity to an uncertainty shock. Clearly, our evidence on a larger impact of uncertainty shocks on real activity extend to all these alternative indicators of the business cycle. Interestingly, our evidence points to a “drop, rebound, and overshoot” effect of uncertainty shocks, which is consistent with a “wait-and-see” optimal behavior in response to an increase in uncertainty (Bloom, 2009).

4.3. Omitted variables/Cholesky ordering

Our results may be spurious in the presence of 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 anticipated effects of uncertainty shocks. Christiano et al. (2014) 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. The robustness of our results to various perturbations of the baseline vector is checked. Such perturbations are presented and motivated below.

4.3.1. 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 aggregate demand and inflation (for instance, because of financial wealth-related effects in a sticky-price context as in Castelnuovo and Nisticò, 2010). Since in our sample the correlation between the VIX and the log of the S&P500 is 0.28, our baseline model might mix up variations in uncertainty with variations in the level of the stock market index. We then consider the five-variate VAR \( \mathbf{X}_t^{S&P500} = [S&P500_t, \text{vix}_t, \pi_t, \text{un}_t, R_t]' \), where “S&P500” captures the log of S&P500 (source: Federal Reserve Bank of St. Louis’ website).\(^{11}\)

4.3.2. 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. To this aim, the following five-variate VAR is considered: \( \mathbf{X}_t^{TFP} = [\text{TFP}_t, \text{vix}_t, \pi_t, \text{un}_t, R_t]' \), where “TFP” is the log of the total factor productivity measure proposed by Fernald (2012). The series is adjusted to control for variations in factor utilization as in Basu et al. (2006). The source of the data is the Federal Reserve Bank of San Francisco’s website.\(^{12}\)

4.3.3. 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). 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. This issue is scrutinized by estimating the five-variate VAR \( \mathbf{X}_t^{sent} = [\text{sent}_t, \text{vix}_t, \pi_t, \text{un}_t, R_t]' \), where “sent” stands for consumer sentiment.

4.3.4. FAVAR
A way to tackle the informational insufficiency issue, popularized by Bernanke et al. (2005), is to add a factor extracted from a large dataset to our VAR, so to purge the (possibly bias-contaminated) estimated shocks. A large dataset composed of 150 time-series is then considered, 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 Caggiano et al., 2013). 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 \( \mathbf{X}_t^{lovvar} = [f_1^{lov}, \text{vix}_t, \pi_t, \text{un}_t, R_t]' \), where “\( f_1^{lov} \)” is the factor explaining the largest share of variance of the series in our enlarged database.\(^{13}\)

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\(^{11}\) The S&P500 displays a distinct up-trending behavior in the sample. Our VAR is estimated by employing a cubically detrended measure of (the log of S&P500 (Bloom, 2009; Jurado et al., 2013). Hodrick–Prescott filter applied the log of the S&P500 index to isolate its cyclical component. Our results are similar when a Hodrick–Prescott filter (smoothing weight: 1600) is applied to the stock market index.

\(^{12}\) The (log of) TFP measure is HP-filtered (smoothing weight: 1600) to preserve the same degree of integration of the other variables in the VAR.

\(^{13}\) 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 Okun’s law 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).
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, uncertainty is ordered last in our vector, i.e., \( X_{\text{unc last}} = [\pi_t, u_t, R_t, vix_t]^T \). 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, the macroeconomic variables modeled with our VAR are forced to have a zero on-impact reaction to uncertainty shocks.

The outcome of all robustness checks are reported in Fig. 7. In all cases, the recessionary evolution of the unemployment rate is 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.\(^{14}\)

Importantly, the role of non-linearities turns out to be supported also by our sensitivity analysis. Fig. 8 shows the difference between the predictions of linear and non-linear VARs in each of the cases previously shown in Fig. 7. In particular, it focuses on the two policy-relevant variables in our analysis, i.e., unemployment and inflation. While some

\(^{14}\) 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. The exploration of the relationships among firm risk, aggregate uncertainty, and aggregate productivity is left to future research.
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 investigation. Quantitatively, the indications coming from the VARs are very similar.

4.4. Conditionally-linear IRFs

As in Auerbach and Gorodnichenko (2012), the computation of our IRFs is undertaken by assuming to remain in a recessionary state after the uncertainty shock has hit the economic system. Ramey and Zubairy (2013) criticize Auerbach and Gorodnichenko’s (2012) computation of the macroeconomic IRFs to a positive fiscal spending shock. An expansionary shock, their argument goes, is likely to help the economy out of a recession. Hence, the omission of the possibility of switching from a regime to another could be a source of bias. We believe that Ramey and Zubairy’s (2013) critique hardly applies to our case. Our analysis quantifies the effects of a contractionary shock such as an exogenous increase in uncertainty on unemployment in recessions. Hence, our assumption of remaining in the same phase of the business cycle after the shock is somewhat natural. It also enables us to enjoy a computational benefit, since it simplifies the calculation of IRFs and makes them independent with respect to sign, size and history of the shocks. An experiment based on Generalized IRFs that account for the feedback going from the evolution of our transition variable (included in our set of endogenous variables in this experiment) to the probability of recession shows that our main result, i.e., that the real effects of uncertainty shocks are larger in recessions, turns out to be fully confirmed (see Caggiano et al., 2013).

5. FEVDs

Finally, the contribution of uncertainty shocks for the dynamics of the variables of interest by performing a forecast error variance decomposition is assessed. 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%), but negligible 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 analysis by Vavra (2014). He studies price-setting models with volatility shocks, and shows that greater volatility leads to an increase in aggregate price flexibility. Consequently, a nominal stimulus mostly generates inflation rather than output growth. Since volatility is countercyclical, this implies that monetary stimulus has smaller real effects during recessions. Vavra (2014) shows that his models matches a variety of facts in CPI micro data that standard price-setting models miss. Empirical support to the prediction of policy shocks being less important for the dynamics of the real side of the economy when uncertainty is high is also offered by Aastveit et al. (2013) and Pellegrino (2014), who work with non-linear VARs and macroeconomic data for a number of countries, including the United States.

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. Table 2 collects the contribution of uncertainty shocks conditional on our five-variate model with S&P500, and contrasts 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%). 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).

6. Conclusions

What are the effects of uncertainty shocks on unemployment dynamics? We answer this question by estimating non-linear (Smooth-Transition) VARs with post-WWII U.S. data. Such effects are found 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. Inflation is also found to display a stronger reaction 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. An implication of these findings is that linear models mixing up recessions and non-recessionary phases may substantially downplay the effects triggered by uncertainty shocks.

From a modeling standpoint, our results support frameworks with sticky prices, which have been shown to help micro-founded DSGE models to replicate the comovements involving output and its components conditional on an uncertainty shock (Basu and Bundick, 2012). Moreover, our results lend support to the modeling of real frictions on the labor market, which are key for replicating the response of unemployment to uncertainty hikes, above all when combined with nominal price frictions (Leduc and Liu, 2013). Finally, our evidence points to a stronger effect of uncertainty shocks in the presence of the zero-lower bound, a prediction in line with the theoretical investigations by Basu and Bundick (2012) and Johannsen (2013).

Acknowledgments

We thank Giorgio Primiceri (Associate Editor) and an anonymous referee for their very useful comments. We also thank Guido Ascarì, Christian Bayer, Sandra Eickmeier, Martin Ellison, Steffen Elstner, Ana Galvão, Kylejurado, Riccardo Lucchetti, Bartosz Mackowiak, Sophocles Mavroeidis, Serena Ng, Irina Panosvka, Evi Pappa, Raffaella Santolini, Konstantinos Theodoridis and participants to seminars held at the Universities of Helsinki, Oxford, Politecnica delle Marche, the Bank of Finland, and presentations held at the XXI International Conference on Money, Banking and Finance (Luis, Rome), the 21st Symposium of the Society for Non-linear Dynamics and Econometrics (Bicocca University, Milan), the Eighth BMRC-QASS Conference on Macro and Financial Economics (Brunel University), and the Padova Macroeconomics Meetings 2013 for their useful feedbacks. Gabriela Nodari provided excellent research assistance. Part of this research was conducted while the first author was visiting Columbia University, whose kind hospitality is gratefully acknowledged. The opinions expressed in this paper do not necessarily reflect those of the Bank of Finland. All remaining errors are ours.

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