Confidence and the Transmission of Macroeconomic Uncertainty in U.S. Recessions

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Abstract

This paper studies the role of confidence in the transmission of uncertainty shocks during U.S. recessions. I use smooth-transition VAR to examine the regime-dependent effect of uncertainty shocks, and a counterfactual decomposition to isolate the role of confidence when the economy is in different regimes, recessions and non-recessions. I find that shutting down the confidence channel leads to greatly dampened and less persistent effects of uncertainty shocks, especially during recessions. I also find that the cross-regime difference in the role of confidence can largely explain the cross-regime short-run difference in the effects of uncertainty shocks.

JEL Classifications: E23, E32, E37, C32, C53

Keywords: uncertainty shocks, confidence, recessions, smooth-transition VAR

1 Introduction

This paper studies the significance of the confidence channel in the transmission of uncertainty shocks during U.S. recessions, and it explores the role of confidence in explaining the observed difference in the real effects of uncertainty shocks across the states of the economy.

Between 2007 and 2009, the U.S. economy experienced an elevation in uncertainty and the most significant economic downturn since the Great Depression. Since then, a large literature has been concerned with the role of uncertainty in economic fluctuations, including [Bloom (2009)].
Bachmann et al. (2013), Baker et al. (2013), Leduc and Liu (2015), and many others. With mostly
dynamic stochastic general equilibrium (DSGE) models or linear vector-autoregression (VAR)
models, the literature generally finds a significant negative impact on economic activity following
an unexpected increase in uncertainty. Caggiano et al. (2014) and Popp and Zhang (2015) find an
asymmetric real effect of uncertainty shocks across business cycles using nonlinear VARs. Mean-
while, others highlight the relationship between confidence and economic fundamentals (Farmer
(1999)), and suggest confidence as an important propagation mechanism for policy shocks (Bach-
mann and Sims (2012)). Bloom (2014) and Ilut and Schneider (2014) propose confidence as a reason
for uncertainty shocks to matter. The objective of the paper is to empirically examine the role of
confidence in the transmission of uncertainty shocks to real economic activity, particularly during
U.S. recessions.

The paper has three main empirical findings. First, the confidence channel plays a signifi-
cant role in transmitting the real effect of uncertainty shocks at all times. Removing the indirect
effect of uncertainty shocks channeled through confidence leads to greatly dampened and less
persistent effects on output. Second, by isolating the shock effect during recession episodes, I find
that the confidence channel of uncertainty shocks is more important during recessions than non-
recessions. The propagation through confidence leads to a sharper decline of output in the short
run and a less persistent output response in the long run when shocks occur during recessions.
Following a standard deviation increase in uncertainty, proxied by the indicator constructed in \(^{\text{Jurado et al. (2015)}}\), eliminating the influence of confidence channel leads to a maximum reduction of
output response by 38.9 percent during recessions relative to 26.8 percent during non-recessions.
Third, the cross-regime difference in the role of confidence can largely explain the observed cross-
regime difference in the effect of uncertainty shocks in the short run. As illustrated in \(^{\text{Caggiano et al. (2014)}}\) and \(^{\text{Popp and Zhang (2015)}}\), uncertainty shocks have generally greater real impacts
during recessions than non-recessions. However, after controlling for the endogenous response of
confidence, uncertainty shocks have similar effects on output in the short run during both regimes.
The results are robust to a variety of model specifications and measurements.

I isolate the effect of uncertainty shocks during recessions by modeling the dynamic behavior
of uncertainty, confidence, output, and other standard macroeconomic variables using a smooth-
transition VAR (ST-VAR) model. ST-VAR models assume the transition across regimes is smooth,
and they can be conveniently used to separate the shock dynamics in different regimes, while
retaining sufficient information to obtain credible estimates in a richly parameterized VAR frame-
work. I compare the predictions of the nonlinear ST-VAR models conditional on recessions to
those predicted by a standard linear VAR to uncover the importance of nonlinearity and to un-
derstand the difference in dynamics following uncertainty shocks across different states of the
economy. The models are estimated using U.S. monthly data from 1968:5 - 2014:12.

To estimate the importance of the confidence channel, I utilize a counterfactual decomposition
approach as used in [Bernanke et al. (1997), Sims and Zha (2006), Kilian and Lewis (2011), and
Bachmann and Sims (2012)]. The idea is to separate the direct effect of an uncertainty shock on
output and the indirect effect of the shock caused by endogenous responses in confidence, which
in turn affects output. After obtaining the baseline impulse responses, I then construct hypotheti-
cal impulse responses in which output and other macroeconomic variables react to an uncertainty
shock as they would with only the indirect effect transmitted by the endogenous response in
confidence shut down. I then compare the hypothetical impulse response of the macroeconomic
variables to the actual impulse response of the variables to draw insights on the role of the con-
fidence channel in the transmission of uncertainty shocks. I apply this approach to the nonlinear
ST-VAR conditional on recessions and a standard linear VAR to understand the importance of the
confidence channel across business cycles.

Confidence matters in the transmission of uncertainty shocks for a number of reasons. First, as
argued by [Akerlof and Shiller (2010), consumer and business confidence reflect sentiments ("ani-
mal spirits"), which can be important sources of economic fluctuations. An increase in aggregate
uncertainty signals worse economic conditions to economic agents, which lowers sentiment and
sentiment-induced spending, leading to falling aggregate demand and an economic contraction.
Second, the confidence channel can also play a role as elevated uncertainty increases risk and
ambiguity. The increased ambiguity makes it difficult for economic agents to form a probability
distribution of economic fundamentals. With pessimistic beliefs, people expect the worst outcome
might occur, which is worsened with the increased uncertainty, leading to further contractions in
investment, spending, and hiring ([Ilut and Schneider (2014)]. In addition, movements in mea-
sured confidence also reflect changes in perceptions about future economic fundamentals. As
discussed in [Barsky and Sims (2012), confidence conveys information about future productivity
growth and output changes at lower frequencies. An increase in uncertainty increases the real op-
tion value for economic agents to delay their spending and investment activities ([Bloom (2009)],
making them less sensitive to changes in economic conditions and policies, thereby leading to
misallocation resources among firms, lowered productivity and lower output overall.

The paper contributes to three literatures. The paper bridges the literature that studies uncer-
tainty shocks\(^1\) and the literature that studies the role of confidence\(^2\) by studying the interactions between uncertainty and confidence when the economy is in different regimes. It examines the role of confidence channel in the propagation of uncertainty shocks and quantifying the importance of the channel. The paper also contributes to the literature that studies asymmetric effects of uncertainty shocks across business cycles\(^3\) by exploring the cross-regime difference in the role of confidence in explaining the observed cross-regime difference in shock dynamics.

The rest of the paper is organized as follows. Section 2 presents an overview of the empirical model, describes the data, and presents the identification and estimation methodology. Section 3 reports the main empirical results. Section 4 performs robustness checks. Section 5 concludes.

## 2 Econometric Framework

This section describes my econometric framework. Section 2.1 presents the empirical model. Section 2.2 describes the data and measurements. Section 2.3 provides details on the identification and estimation strategy. Section 2.4 presents the method to isolate the role of the confidence channel in transmitting the effect of uncertainty shocks.

### 2.1 Empirical Model

To allow for regime-dependent responses between recessions and non-recessions, I use a regime-dependent vector-autoregression (VAR) where the transitions across states are smooth. The model is similar to the smooth-transition vector-autoregression model (ST-VAR) developed by Auerbach and Gorodnichenko (2012) to study fiscal policy shocks. The main advantage of modeling regime dependency using ST-VAR relative to estimating VAR separately for each regime is that a particular regime, such as recessions, may have relatively few observations for the estimation, which leads to less precise and unstable estimates. By comparison, as ST-VAR exploits only the variation in degree of being in a particular regime, the method utilizes more information from a larger

\(^1\)For example, Bloom (2009), Basu and Bundick (2012), Christiano et al. (2014), Gilchrist et al. (2014), Ilut and Schneider (2014), and Leduc and Liu (2015).

\(^2\)For example, Farmer (1999), Akerlof and Shiller (2010), Barsky and Sims (2012), and Bachmann and Sims (2012).

\(^3\)Caggiano et al. (2014) and Popp and Zhang (2015).
number of observations, which leads to more precise estimates. The model is specified as follows:

\[
X_t = F(z_{t-1})\Pi_R(L)X_{t-1} + (1 - F(z_{t-1}))\Pi_{NR}(L)X_{t-1} + u_t, \tag{1}
\]

\[
u_t \sim N(0, \Omega_t), \tag{2}
\]

\[
\Omega_t = F(z_{t-1})\Omega_R + (1 - F(z_{t}))\Omega_{NR}, \tag{3}
\]

\[
F(z_t) = \frac{\exp(-\gamma z_t)}{1 + \exp(-\gamma z_t)}, \gamma > 0, \text{ var}(z_t) = 1, \text{ E}(z_t) = 0. \tag{4}
\]

\[X_t\] is a \(N \times 1\) vector of macroeconomic variables used in the VAR estimation. As I will be interested in characterizing the effect of uncertainty shocks and role of confidence in the transmission of the shocks, I let \(X_t\) include a measure of uncertainty, \(U\), a measure of confidence, \(Conf\), and a measure of overall economic activity proxied by industrial production index, \(IP\). \(z\) is a transition indicator. \(F(z_{t-1})\) is a logistic transition function that captures the probability of being in recessions (\(R\)) versus non-recessions (\(NR\)), whose smoothness is characterized by \(\gamma\). \(\Pi_R(L)\) and \(\Pi_{NR}(L)\) are regime-dependent lag polynomials of finite order \(d\). \(u\) is a vector of reduced-form residuals with mean zero and time-varying, regime-dependent covariance matrix \(\Omega_t\). \(\Omega_R\) and \(\Omega_{NR}\) are the covariance matrices of the residuals computed during recession and non-recessions respectively.

Intuitively, the model assumes that the dynamics of \(X\) can be described by a linear combination of two linear VARs: one suited to describe the dynamics during recessions, and the other suited to describe the dynamics during non-recessions. \(F(z)\), bounded between 0 and 1, characterizes the degree of economic contraction or simply the probability of being in the recession regime given observations of \(z\). Small values of \(z\) during economic stress translate into large values of \(F(z)\) near 1, resulting in a heavier weight of the recession-regime VAR in the characterization of the data in these periods. The model nests a standard linear VAR in the limiting cases when \(F(z) = 0\) or \(F(z) = 1\).

The model specified by equation (1) - (4) allows two ways for differences in the propagation of structural shocks across regimes: contemporaneous difference via differences in covariances matrices \(\Omega_R\) and \(\Omega_{NR}\), and dynamic difference via differences in lag polynomials \(\Pi_R(L)\) and \(\Pi_{NR}(L)\).

My baseline model features four lags and three endogenous variables, i.e. \(X_t = [U_t, Conf_t, IP_t]'\). The results are robust to reasonable variations of the number of lags and the number of variables.
I performed a similar test for nonlinearity as in Auerbach and Gorodnichenko (2012) that uses a second order approximation to equation (1) - (4) using lags of $X_t$, $X_t z_{t-1}$, and $X_t z_{t}^2$. Akaike and Bayesian information criteria favor a nonlinear specification in describing the dynamics of $X_t$.

### 2.2 Data and Measurement

The data used in the baseline estimation is from 1968:5 to 2014:12, which covers major post-WWII recessions in the U.S. I use the uncertainty measure developed by Jurado et al. (2015) (JLN) to proxy macroeconomic uncertainty in the baseline analysis. The index is constructed by exploring the common variation in forecast error of a large number of economic indicators to characterize movements in aggregate uncertainty. There are also other popular proxies for uncertainty used in the literature. For example, Bloom (2009) uses the Chicago Board Options Exchange Market Volatility Index (VXO), which measures the implied volatility of the S&P 100 index options. The realized volatility of stock market returns are used as a proxy for uncertainty in Leahy and Whited (1996). Bachmann et al. (2013) consider cross-sectional dispersion of survey-based forecasts (FDISP) constructed using the Federal Reserve Bank of Philadelphia’s Business Outlook Survey. Baker et al. (2013) (BBD) develop a news-based economic policy uncertainty index. As discussed in Jurado et al. (2015), the JLN measurement has two main benefits that lead to a better characterization of uncertainty. First, it is more closely related to variations in macroeconomic fundamentals by utilizing a large number of economic indicators, including stock market series, rather than using a single or a small number of series. Second, the construction of the index removes the forecastable components from the conditional volatilities of the economic indicators, so it avoids mistakenly consider forecastable variations as uncertainty. Table 1 provides summary statistics and pairwise correlation of these uncertainty measures. Figure 1 plots the JLN measure along with other measures of uncertainty.

**Figure 1** goes here.

**Table 1** goes here.

The focus of the paper is on recessions for two reasons. First, the identification of major U.S.

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4 AIC = -6.480 and BIC = -6.063 for a nonlinear model with 4 lags and $U$, $Conf$, and $IP$ as endogenous variables, while AIC = -6.0506 and BIC = -5.8247 for a linear model with equal number of lags and same variables.

5 To obtain the pre-1986 VXO data, I compute the actual monthly standard deviation of the daily S&P 500 index normalized to the same mean and variance as the VXO index when they overlap from 1986 onward, a practice similar to Bloom (2009).
post-WWII recessionary episodes are noncontroversial, and JLN proxied uncertainty peaks only during major recessions. Focusing on recessions allows to obtain cleaner information about how uncertainty shocks affect the macroeconomy. In contrast, expansionary phases are characterized by heterogeneous signals and carry possibly contaminated information on the effects of uncertainty shocks (Caggiano et al. (2014)). Second, focusing on recessions makes the analysis less sensitive to the selection of uncertainty indicators. As shown in Figure 1, all uncertainty indicators have strong comovements during NBER recessions, documenting elevated uncertainties during these phases, but they provide somewhat diverse characterizations of uncertainty during NBER expansionary phases. Jurado et al. (2015) does not recognize any major change in uncertainty during expansions, but the measures based on stock market volatilities document spikes in a few episodes of expansions when there was significant turbulence in the financial markets that lead to an increase in conditional volatility. It is debatable whether these episodes are associated with major increases in the uncertainty of economic fundamentals. As the literature so far has little consensus on which is the best measure of economic uncertainty, and given the diverse characterizations of these measures during NBER expansions, I focus my analysis on the effect of uncertainty shocks during recessions and contrast the results to those predicted by a linear model, which describes a mixed effect of uncertainty shocks during all times. I also consider alternative uncertainty measures based on stock return volatilities to check the robustness of my results.

To measure confidence, I use the diffusion index of future general economic activity from the Manufacturing Business Outlook Survey by the Federal Reserve Bank of Philadelphia in the baseline analysis. The survey asks the manufacturing purchasing managers conducting business in the Third Federal Reserve District about their outlook on the direction of change in overall business activity and in the various measures of activity at their plants. I use the index constructed by taking the percentage difference in the survey responses reporting increases and decreases in general business conditions in the next 6 months. I also consider the index of consumer sentiment by University of Michigan the Survey of Consumers as an alternative measurement.

The transition variable $z$ and transition probability $F(z)$ play a key role in the model. Auerbach and Gorodnichenko (2012) and Bachmann and Sims (2012) model $z$ using a standardized backward-looking 7-quarter moving average of the growth rate of real GDP in their quarterly smooth-transition models. Similarly, I model $z$ to be a 12-month moving average of Industrial Production Index, normalized to have mean zero and rescaled to have unit variance. I calibrate

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6 As discussed in Jurado et al. (2015), these indicators may be contaminated by leverage and investor sentiment.
\( \gamma = 2 \) so that the economy spends about 15 percent of the time in recessions, defined as periods when \( F(z) \geq 0.8 \), same as the NBER business cycle dates in our sample period. Figure 2 plots \( F(z) \). It is clear that the values of \( F(z) \) are highly correlated with NBER business cycles and \( F(z) \geq 0.8 \) roughly replicates NBER recession episodes.

Figure 2 goes here.

The industrial production index is used to characterize macroeconomic activity. The data is transformed using the first log difference to ensure stationarity.

2.3 Estimation and Identification

The identification of exogenous variations in uncertainty in equation (1) is obtained by imposing the Cholesky assumption. As the order of the variables in \( X_t \) is restricted to be \([U_t, Conf_t, IP_t]^t\) in the baseline analysis, it is assumed that uncertainty shocks affect output immediately, whereas uncertainty reacts to other shocks with delay. Meanwhile, confidence is allowed to directly and immediately respond to uncertainty shocks and output is allowed to respond immediately to surprise changes in confidence. Though using a recursive assumption is common among the literature\(^7\), there is little consensus on the ordering given the endogenous nature of the variables. Caggiano et al. (2014) and Leduc and Liu (2015) assume uncertainty is slow-moving to other shocks but can have on-impact effects on inflation, real economic activity, and interest rates, while Bloom (2009) assumes that uncertainty is fast-moving relative to interest rates, prices and real economic activity and has delayed effects on these variables. Furthermore, the relative ordering between \( Conf_t \) and \( U_t \) is debatable given the high correlation between these two variables. To address this concern, I use data of higher frequency in the estimation and consider alternative orderings of \( X_t = [Conf_t, IP_t, U_t]^t \) and \( X_t = [IP_t, U_t, Conf_t]^t \) in the robustness check. The results do not appear to be affected qualitatively by these alternative specifications and short-run timing assumptions.

Given the nonlinearity of the model, I estimate it by the Markov-Chain Monte-Carlo (MCMC) simulation method proposed by Chernozhukov and Hong (2003). Appendix A reports the technical details on the estimation methodology. The method finds a global optimum in terms of model fit under standard conditions and allows for straightforward computation of parameter estimates and confidence intervals. As the model is linear conditional on a regime, absent any feedback

\(^7\)For example, Bloom (2009), Caggiano et al. (2014), Leduc and Liu (2015).
to \( z_t \), the impulse responses to an uncertainty shock can be computed by assuming a linear VAR conditional on regime-specific parameter estimates.

### 2.4 Isolating the Role of Confidence Channel

This section discusses the procedure to isolate the role of confidence in transmitting the effect of uncertainty shocks. The approach is similar to the one used in Bernanke et al. (1997), Sims and Zha (2006), Kilian and Lewis (2011), and Bachmann and Sims (2012).

Let \( X_t = [U_t, Conf_t, IP_t]' \). The identifying assumption on the short-run timing effects of uncertainty shocks allows the model summarized by equation (1) - (4) to be written in the following linear form, conditional on a particular regime:

\[
A_0^{(s)} \begin{bmatrix} U_t \\ Conf_t \\ IP_t \end{bmatrix} = \sum_{j=1}^{d} A_j^{(s)} \begin{bmatrix} U_{t-1} \\ Conf_{t-1} \\ IP_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}, \quad s = 0, 1 \tag{5}
\]

where \( A_0^{(s)} = \begin{bmatrix} 1 & 0 & 0 \\ a_{21}^{(s)} & 1 & 0 \\ a_{31}^{(s)} & a_{32}^{(s)} & 1 \end{bmatrix} \) \( s = 0 \) and \( s = 1 \) are regime indicators for non-recessions and recessions. Parameters with superscript \( (s) \) indicate the parameter estimates conditional on the regime. \( \varepsilon_t = [\varepsilon_{1t}, \varepsilon_{2t}, \varepsilon_{3t}]' \) is a vector of structural shocks and given by \( \varepsilon_t = A_0^{(s)} u_t \) where \( A_0^{(s)} \) is a lower-triangular regime-dependent impact matrix.

Confidence influences the transmission of uncertainty shocks into output (\( IP \)) in two ways. If confidence reacts to uncertainty shocks on impact \( (a_{21}^{(s)} \neq 0) \), and \( IP \) immediately responds to changes in confidence \( (a_{32}^{(s)} \neq 0) \), then \( a_{21}^{(s)} \times a_{32}^{(s)} \) measures the confidence channel of uncertainty shocks on impact. In addition, confidence operates as a propagation mechanism for the dynamic effects of uncertainty shocks. If confidence responds to uncertainty shocks at any horizon, and if \( IP \) responds to lagged changes in confidence, then the dynamic response of confidence to uncertainty shocks will have an effect on the dynamics of \( IP \) to uncertainty shocks.

To study how important the confidence channel is, I construct a hypothetical impulse response of \( X \) in which output reacts to an uncertainty shock as it normally would with only the endogenous response in confidence shut down at all horizons. Intuitively, it can be thought of considering
a hypothetical economy with an identical underlying economic environment, except that the uncertainty shocks are restricted not to affect confidence at any horizon. As the confidence remains fixed in this hypothetical case, there is no more shock transmission through confidence to output. The importance of the confidence channel can thus be isolated by comparing the hypothetical impulse responses to the actual responses.

More compactly, equations (5) - (6) can be rewritten in companion matrix form as VAR(1) by defining $Z_t = [X_t, X_{t-1}, ..., X_{t-d-1}]'$, where $X_t = [U_t, \text{Con}t, \text{IP}_t]'$.

$$Z_t = \Phi(s)Z_{t-1} + \psi_i(s), \quad \Phi(s) = \begin{bmatrix} A_0^{(s)} & A_1 & A_2 & \ldots & A_d \\ I & 0 & 0 & \ldots & 0 \\ 0 & I & 0 & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & \ldots & \ldots & I & 0 \end{bmatrix}, \quad \psi_i(s) = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}.$$  

Let $e_i$ be a $1 \times 3$ selection row vector with a one in the $i$th place and zeros elsewhere. Let $A_0^{(s)}(q)$ be the $q$th column of $A_0^{(s)}$. The impulse response of factor $i$ to a structural shock $q$ at horizon $h$ in regime $s$ is $\delta^{(s)}_{i, q, h} = e_i\Phi(s)h^{-1}A_0^{(s)}(q)$.

The construction of hypothetical impulse responses to fix confidence response at all horizons requires restricting $\delta^{(s)}_{2, 1, h} = 0$, for any $h = 1, ..., H$, where 2 is the position indicator for confidence and 1 is the position indicator of uncertainty. This is achieved by creating a sequence of hypothetical shocks to confidence $\{\tilde{\varepsilon}^{(s)}_{2, h}\}_{h=1}^{H}$ so that $\delta^{(s)}_{2, 1, h} = 0$ in response to a unit shock in $\varepsilon_{1, 1}$ at all horizons. To shut down the contemporaneous effect of uncertainty on confidence on impact, $\tilde{\varepsilon}_{2, 1}$ must satisfy

$$A_0^{(s)}(2, 1) + A_0^{(s)}(2, 2)\tilde{\varepsilon}_{2, 1} = 0, \quad \text{or} \quad \tilde{\varepsilon}_{2, 1} = -\frac{A_0^{(s)}(2, 1)}{A_0^{(s)}(2, 2)}.$$

The subsequent confidence shocks can be computed recursively as

$$\tilde{\varepsilon}_{2, h}^{(s)} = -\frac{\delta^{(s)}_{2, 1, h} + \sum_{j=1}^{h-1} e_2\Phi(s)^{h-j}A_0^{(s)}(2)\tilde{\varepsilon}_{2, j}^{(s)}}{e_2A_0^{(s)}(2)}, \quad h = 2, ..., H.$$

Given $\varepsilon_{1, 1} = 1$ and $\{\tilde{\varepsilon}_{2, h}^{(s)}\}_{h=1}^{H}$, we can construct the hypothetical impulse responses of the vari-
ables in the VAR to the uncertainty shock as

\[ \tilde{\delta}_{i,1,h}^{(s)} = \delta_{i,1,h}^{(s)} + \sum_{j=1}^{h} e_j \Phi_{(s)}^{h-j} A_{0}^{(s)}^{-1} (2) \tilde{\varepsilon}_{2,j}^{(s)}, \quad i = 1, 2, ..., N. \]

\( \tilde{\delta}_{i,1,h} \) are the responses to an uncertainty shock without the confidence transmission channel. Comparing \( \delta_{i,1,h}^{(s)} \) to the baseline response \( \delta_{i,1,h}^{(s)} \) with confidence to a one unit shock in \( U \) characterizes the importance of confidence in transmitting the effect of the shock. That is,

\[ \rho_{i,1} = \delta_{i,1}^{(s)} - \tilde{\delta}_{i,1}^{(s)} \]

quantifies the effect of confidence at horizon \( h = 1, ..., H. \)

3 Results

This section presents the main results of the paper. Section 3.1 presents the responses to an uncertainty shock for both the linear VAR model and nonlinear ST-VAR conditional on recessions. Section 3.2 presents the results for the importance of confidence in transmitting the effect of uncertainty shocks.

3.1 Effect of Uncertainty Shocks

Figure 3 plots the estimated impulse responses to a one unit \(^8\) shock to uncertainty (proxied by JLN). The dashed red lines plot the responses conditional on the recession regime using the ST-VAR. The black solid lines show the responses in the linear specification of the Cholesky-identified VAR, which characterizes the economy under normal economic times. The grey and pink areas are 68% bootstrapped confidence bands in the linear VAR and ST-VAR respectively.

During both recessions and normal times (proxied by the results under a linear VAR), confidence and output fall significantly and persistently, and follow hump-shaped paths before returning to their steady-states. As output is measured by the first log-difference of industrial production normalized to have zero mean and unit variance, one unit change in output can be

\(^8\) Also it is a one-standard-deviation shock, as I normalize the JLN measurement to have zero mean and unit variance.
interpreted as a standard deviation change in the IP growth rate. No overshooting in output is observed, which is consistent with Jurado et al. (2015). The negative output response is also in line with those obtained in Bloom (2009), Leduc and Liu (2015), and many other empirical studies on uncertainty shocks.

However, uncertainty shocks have quantitatively very different results in the short run between recessions and normal economic times. Compare the two responses in Figure 3, uncertainty shocks that occurred during recessions lead to sharper declines in output but have less persistent effects on the variable. Output falls by a maximum of 1.55 standard deviations during normal times but the same shock leads to a maximum reduction of 1.88 during recessions. A similar pattern is also found for confidence responses. The difference is statistically significant. This finding suggests that uncertainty shocks seem to have more severe and sharper impacts on real economic activity in the short run when the economy is already experiencing a recession. The finding is consistent with Caggiano et al. (2014) that finds uncertainty shocks have greater effects on the U.S. labor market during recessions, and Popp and Zhang (2015) that finds uncertainty shocks lead to sharper responses of a large panel of real economic indicators during recessions using dynamic factor analysis. As shown in the next section, the cross-regime difference in the impulse responses can be largely explained by the difference in the role of confidence.

3.2 The Role of Confidence during Recessions

To quantify the importance of confidence in transmitting the effect of uncertainty shocks, I compare the baseline output responses to the hypothetical responses holding the response of confidence fixed at zero, constructed using the method described in Section 2.4.

Figure 4 reports hypothetical responses holding the response of confidence fixed at zero (dashed green), and contrasts them with the responses with the confidence channel (solid red), conditional on the recession regime. A similar procedure is performed for the linear model to obtain the hypothetical responses during normal times (dotted blue).

Table 2 quantifies the output responses to uncertainty shocks during normal and recessions times with and without allowing the role of confidence in the shock transmission. The impact effect

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9 As discussed in Jurado et al. (2015), when we proxy uncertainty using their measurement (JLN), no overshooting behavior arises.
is measured by the impact response of output to the uncertainty shock divided by the impact size of the shock (normalized to one). The maximum impact and cumulative impact are defined similarly. Instead of using impact response, I use the maximum responses (in absolute size) over 60 months to define maximum impact. For cumulative impact, I use the sum of output response over 60 months divided by the sum of uncertainty response.

Table 2 goes here.

Figure 4 and Table 2 illustrate three main results of the paper.

First, without confidence, uncertainty shocks have much smaller and less persistent effects on output growth, and the difference is statistically significant. The result suggests that confidence plays an important role in the transmission of uncertainty shocks both during U.S. recessions and normal times. According to the results in Table 2, shutting down the confidence channel in recessions leads to a major reduction in the impact response, the maximum response, and the cumulative response compared to the baseline model. A similar pattern is also found during normal times. I also consider alternative specifications with different ordering of endogenous variables in the model. The results are quantitatively and qualitatively similar across these specifications.

Second, though confidence plays a non-negligible role in the transmission of uncertainty shocks in both cases, confidence is much more important in the short run during recessions, but appears to have less persistent effects in the medium and long run relative to normal times. As reported in Table 2, shutting down the confidence channel in recessions leads to 37 percent, 39 percent, and 49 percent reduction in the impact response, the maximum response, and the cumulative response compared to the baseline model that allows the role of confidence, relative to 34, 27, and 52 percent respectively during normal times. Though the confidence channel has smaller short run effects during normal times, it explains a 52 percent difference in the cumulative output response to uncertainty shocks during normal times, compared to 49 percent in the recession case, suggesting a more persistent role of confidence during normal times. Similar results are obtained in other specifications.

To see this result more explicitly, Figure 5 plots $\rho_{3,1,h}$, the difference between the actual output response ($\delta_{3,1,h}$) and hypothetical output responses ($\tilde{\delta}_{3,1,h}$) with confidence held constant, to a one unit shock in uncertainty. $\rho_{3,1,h}$ characterizes the importance of confidence at all horizons following a uncertainty shock. According to Figure 6, the confidence channel is responsible for contributing to a sharper decline in output in the short run following an uncertainty shock that
occurs during recessions than during normal economic times, but the importance diminishes over time. In the medium and long run (after 20 months) after the shock, the confidence channel has less persistent effects during recessions relative to normal times.

Figure 5 goes here.

Third, the cross-regime difference in the role of confidence largely explains the cross-regime difference in the output responses to uncertainty shocks within 10 months after the shocks. As shown in Figure 5, after controlling for the response of confidence, the difference in the response of output in the short run is much smaller than the baseline models between normal (dotted blue) and recession times (dashed green). Figure 6 plots the maximum impact (in absolute size) on output across time using the historical observations on $z_{t-1}$. The solid line graphs the historical maximum output response to an uncertainty shock, and the dashed line graphs the maximum output response where confidence is held constant. Output responded more sharply in every major NBER recession episodes after 1968. The maximum output responses during recessions are usually in the neighborhood of 1.8 standard deviations, while they are around 1.4 during non-recessions. After controlling for the response of confidence, output responded by a maximum around 1.17 standard deviations in both regimes. This result suggests that the role of confidence can explain a large part of the difference in the response of output to uncertainty shocks across regimes found in the literature.

Figure 6 goes here.

Why might confidence matter for the transmission of uncertainty shocks? As argued by Akerlof and Shiller (2010), "animal spirits" in consumer and business confidence are important sources of business cycles, as aggregate sentiment determines aggregate spending and aggregate demand, which in turn affects aggregate output and employment. Historically, aggregate uncertainty was elevated only during recessions and most turbulent times in the financial markets, so an unexpected increase in aggregate uncertainty signals declining financial and labor market conditions and a weakening economy overall to consumers and businesses. The signals lower sentiment and sentiment-induced spending, leading to falling demand and an economic contraction.

The confidence channel also plays a role when uncertainty increases risk and ambiguity. Risk

\[^{10}\text{ST-VAR allows the estimated parameters and responses to vary continuously with the state of the economy. One can compute the impulse responses for any value of } z_{t-1}.\]
increases in response to elevated aggregate uncertainty. Also, in a world of information frictions, an increase in uncertainty makes it more difficult for economic agents to learn information about economic fundamentals, increasing the risk of having larger learning errors (Mackowiak and Wiederholt (2011)). When uncertainty increases, which makes it difficult for economic agents to form a probability distribution, and when some agents have pessimistic beliefs due to lack of confidence, they act as if the worst outcome would occur (Ilut and Schneider (2014)), which is worsened by the increased uncertainty. As economic agents expect a worse outcome in the future, they reduce investment and spending, which can also lead to a real contraction.

In addition, movements in measured confidence also reflect changes in perceptions about future economic fundamentals. As discussed in Barsky and Sims (2012), confidence conveys information about future productivity growth and output changes at lower frequencies. An increase in uncertainty increases the real option value for economic agents to delay their spending and investment activities, making them less sensitive to changes in economic conditions and policies, thereby leads to misallocation resources among firms, lowered productivity and lower output overall (Bloom (2009)).

4 Robustness

To provide a robustness analysis of the results described above, I estimate the model under alternative measurements and alternative model specifications.

4.1 Alternative Measurements

As there is no direct measure of uncertainty, the literature has mainly relied on proxies or indicators of uncertainty. This paper uses index constructed by Jurado et al. (2015) in the baseline estimation. There are also other popular uncertainty indicators, including the implied and realized stock market volatilities. I consider two alternative indicators for uncertainty based on stock market volatilities to check the robustness of the results. First, I consider the VXO index as a proxy for uncertainty as in Bloom (2009). As the pre-1986 VXO index is not available, I replaced the pre-1986 index using the realized stock return volatility, normalized to have the same mean and variance as VXO from 1986 onward, a practice similar to Bloom (2009). I also show the robustness of our results with respect to the realized volatility of S&P 500 returns (StockVol), a proxy used in Caldara et al. (2014). The cross-regime impulse responses of confidence and output to a unit
shock to these uncertainty measures are reported in the solid lines in Figure 7 and Figure 8. The
dashed lines and dotted lines report the restricted impulse responses of output when confidence
is held fixed.

\textit{Figure 7 goes here.}

\textit{Figure 8 goes here.}

A unit shock to JLN is quantitatively more important and has more persistent effects than a shock
to VXO or realized volatility to stock returns, mainly due to the difference in the statistical prop-
erties of these measures. Despite this difference, the main results are qualitatively robust. The
three main results are qualitatively consistent to those in the baseline analysis: (1) the confidence
channel is important in the transmission of uncertainty shocks in both cases; (2) the contribution
of the confidence channel in the short run is significantly larger in recessions; (3) the short-run
cross-regime dispersion in the output responses to uncertainty shocks can be largely explained by
the difference in the role of confidence.

I also consider an alternative measurement for confidence using index of consumer sentiment
by University of Michigan the Survey of Consumers (UMCSENT). The index measures confidence
by surveying consumers from 48 states and the District of Columbia regarding their expectations
on overall economic activity, personal finance, and buying plans. The sample is truncated to be
1978:1 - 2014:12 due to the availability of UMCSENT at monthly frequency. As Figure 9 shows,
the results are qualitatively robust to this measurement.

\textit{Figure 9 goes here.}

4.2 Alternative Cholesky Ordering

Our identification strategy is based on a recursive Cholesky assumption, with uncertainty ordered
first before confidence and output. Though common in the literature, the assumption is debatable.
I address this issue by checking the robustness of my results using alternative recursive assump-
tions.

I consider ordering uncertainty in the second and the third place in the 3-variable VAR. I
also consider reversing the positions between output and confidence. The system $\xi_1$ is esti-
mated in three alternative ordering of endogenous variables: $X_t = [Conf_t, IP_t, U_t]'$ and $X_t =$
Results are reported in Figure 10 and Figure 11. These alternative identifications produce impulse responses similar to the baseline specification.

4.3 Alternative Transition Indicator

I model the transition indicator $z$ using a standardized backward-looking 12-month moving average of the growth rate of Industrial Production Index, normalized to have mean zero and rescaled to have unit variance. Though the approach is consistent with the literature including Auerbach and Gorodnichenko (2012), I use a 12 month moving average of IP rather than the 7-quarter moving average of real GDP that this literature uses. The reason is that I use monthly data and measure real economic activity using industrial production. By carefully examining the behavior of the transition probability $F(z)$ constructed using industrial production, I find a 12-month moving average better replicates the dates of NBER business cycles than a 21-month moving average, though there are more "flips" when $z$ is constructed based on a 12-month average. Figure 12 plots this alternative indicator constructed using 21-month moving average of IP. $\gamma$ is calibrated to be 1.4 to produce same number of NBER recession months. To be consistent with the literature, I also consider this alternative transition indicator in the robustness check. The results are reported in the Figure 13. The results do not appear to be sensitive to the alternative identification of transition indicator.

4.4 Omitted Variables

The baseline is modeled using linear VAR and ST-VAR with three variables, a measure of uncertainty, a measure of confidence, and a measure of real economic activity. As discussed in the literature of VAR models, an VAR model that is not embedded with sufficient information can lead to misidentification of shocks and distorted shock responses. To address this concern, I expand the baseline vector to include possibly omitted variables for better capturing the relationship
between the endogenous variables and better identification of uncertainty shocks.

Adding Nominal and Financial Variables  I first expand the baseline vector to include possibly omitted nominal and financial variables. The models are expanded to include five variables\footnote{Including more variables allows more information in the VAR, but it also expands the parameter space, making it more difficult to obtain stable and credible estimates.} including federal funds rate and S&P 500 returns, i.e. \( X_t = [U_t, Conf_t, IP_t, FFR_t, S&\text{P}500_t]' \). The results are reported in Figure 14.

FAVAR  As discusses in the factor-augmented VAR (FAVAR) literature, another way to address the omitted information problem in VARs is to consider a factor structure with the factors extracted using the information from a large dataset. I use the FRED-MD dataset, a collection of publicly available U.S. monthly data series described in McCracken and Ng (2015). The dataset includes a large panel of economic indicators of output, income, labor market, consumption, housing, orders, money, prices, interest rates, and stock market. I extract two common factors using principal components, which explain the maximum share of variance of the data series. I then augment the vector to include the principal component estimates, i.e. \( X_t = [F1_t, F2_t, U_t, Conf_t, IP_t]' \). This procedure is similar to the practice of Stock and Watson (2002) and Bernanke et al. (2005). Figure 15 reports the impulse responses with and without the confidence channel in normal and recession cases.

5 Conclusion

This paper focuses on the role of confidence in the transmission of uncertainty shocks in U.S. recessions. To distinguish the dynamics following uncertainty shocks during recessions and non-recessions, I use a smooth-transition VAR where the parameters depend on the state of the economy and the transition across the states is smooth. I then use a counterfactual decomposition approach to isolate the importance of the confidence channel. Intuitively, the indirect effect of uncertainty shocks caused by the endogenous response in the confidence is removed, and the impulse responses are compared to the baseline responses where the role of confidence channel is not restricted.
The paper has three main empirical findings. First, confidence appears to play an important role in the transmission of uncertainty shocks, both during U.S. recessions and normal economic times. In both the linear VAR specification and the ST-VAR specification conditional on recessions, removing the confidence channel reduces the effect of uncertainty shocks significantly. Second, the confidence channel of uncertainty shocks is more important in the transmission of uncertainty shocks during recessions, especially in the short run. Removing the indirect effect transmitted through the confidence channel greatly reduces the overall effect of uncertainty shocks in the short run during recessions than during non-recessions. Third, the difference in the role of confidence in the short run can largely explain the documented cross-regime difference in the effect of uncertainty shocks. After restricting confidence not to move in response to uncertainty shocks, uncertainty shocks have similar quantitative effects in the short run between recessions and non-recessions. The results provide empirical facts for future theoretical studies of uncertainty shocks and their transmission channels.

Though our results suggest that confidence is an important channel for the transmission of uncertainty shocks, it is not the exclusive channel for uncertainty shocks to matter. Uncertainty shocks have dampened but still significant effects on real economic activity after the role of confidence is isolated, suggesting other channels, such as the real-option mechanism, financial conditions, and precautionary saving, are also likely to be important in explaining the real effects of uncertainty shocks.

**Bibliography**


Appendix

A Estimation Procedure for ST-VAR

This section discusses the estimation procedure for our model (1) - (4). The method is similar to Auerbach and Gorodnichenko (2012). Due to the nonlinearity of the problem and the dimension of parameters, I use a Markov-Chain Monte-Carlo (MCMC) algorithm in the estimation and the construction of confidence intervals.

The log likelihood for model (1) - (4) is given by

\[ \log L = \text{const} - \frac{1}{2} \sum_{t=1}^{T} \log |\Omega_t| - \frac{1}{2} \sum_{t=1}^{T} u_t' \Omega_t^{-1} u_t, \]  

(7)

where \( u_t = \Phi_t - (1 - F(z_{t-1}))\Pi_{NR}(L)X_{t-1} - F(z_{t-1})\Pi_R(L)X_{t-1} \) and \( \Omega_t = F(z_{t-1})\Omega_R + (1 - F(z_t))\Omega_{NR} \). The parameters that need to be estimated are \( \Psi = \{\Pi_R(L), \Pi_{NR}(L), \Omega_R, \Omega_{NR}\} \). More compactly, we can write \( u_t = \Phi_t - \Pi W_t' \), where \( \Pi = [\Pi_R(L) \Pi_{NR}(L)] \) and \( W_t = [F(z_{t-1})X_{t-1} (1 - F(z_{t-1}))X_{t-1} \ldots F(z_{t-p})X_{t-p} (1 - F(z_{t-p}))X_{t-p}] \).

Note that conditional on \( \{\Omega_R, \Omega_{NR}\} \), the model is linear in lag polynomials \( \{\Pi_R(L), \Pi_{NR}(L)\} \). Thus I can separate the parameters into two blocks in the estimation.

For a given guess of \( \{\Omega_R, \Omega_{NR}\} \), lag polynomials \( \{\Pi_R(L), \Pi_{NR}(L)\} \) can be estimated by weighted least squares where weights are given by \( \Omega_t^{-1} \). That is, I solve a minimization problem of

\[ \frac{1}{2} \sum_{t=1}^{T} u_t' \Omega_t^{-1} u_t = \frac{1}{2} \sum_{t=1}^{T} (X_t - \Pi W_t')' \Omega_t^{-1} (X_t - \Pi W_t') \]

\[ = \text{trace} \left[ \frac{1}{2} \sum_{t=1}^{T} (X_t - \Pi W_t')' \Omega_t^{-1} (X_t - \Pi W_t') \right] \]

\[ = \text{trace} \left[ \frac{1}{2} \sum_{t=1}^{T} (X_t - \Pi W_t')' (X_t - \Pi W_t') \Omega_t^{-1} \right]. \]

The first order condition with respect to \( \Pi \) is \( \sum_{t=1}^{T} (W_t' X_t \Omega_t^{-1} - W_t' W_t \Pi' \Omega_t^{-1}) = 0 \), which yields

\[ \text{vec} \left( \sum_{t=1}^{T} W_t' X_t \Omega_t^{-1} \right) = \text{vec} \left( \sum_{t=1}^{T} W_t' W_t \Pi' \Omega_t^{-1} \right) \]

\[ = \sum_{t=1}^{T} \text{vec} (W_t' W_t \Pi' \Omega_t^{-1}), \]

so
\[
\text{vec}(\sum_{t=1}^{T} W'_t X_t \Omega_t^{-1}) = \sum_{t=1}^{T} \text{vec}(\Pi'_t)[\Omega_t^{-1} \otimes W'_t W_t]
\]

\[
= \text{vec}(\Pi'_t) \sum_{t=1}^{T} [\Omega_t^{-1} \otimes W'_t W_t],
\]

or \[
\text{vec}(\Pi'_t) = (\sum_{t=1}^{T} [\Omega_t^{-1} \otimes W'_t W_t])^{-1} \text{vec}(\sum_{t=1}^{T} W'_t C_t \Omega_t^{-1}).
\]

The procedure iterates over different sets of values of \(\{\Omega_R, \Omega_{NR}\}\) until a maximum is reached for (7). To ensure \(\{\Omega_R, \Omega_{NR}\}\) are positive definite, I let \(\Psi = [\Pi_R(L), \Pi_{NR}(L), \text{chol}(\Omega_R), \text{chol}(\Omega_{NR})]\) in the iteration, where \(\text{chol}\) is the operator for Cholesky decomposition. Following Auerbach and Gorodnichenko (2012), I use Metropolis-Hastings algorithm to implement the MCMC. The method delivers a global optimum and posterior distributions of parameter estimates. The chains are constructed in the following steps:

1. Draw a candidate vector of parameter values \(\Theta^{(n)} = \Psi^{(n)} + \psi^{(n)}\) for the chain’s \(n + 1\) state, where \(\Psi^{(n)}\) is current state, \(\psi^{(n)}\) is a vector of i.i.d. shocks draw from \(N(0, \Omega_{\psi})\). \(\Omega_{\psi}\) is diagonal.

2. Take the \(n + 1\) state of the chain as

\[
\Psi^{(n+1)} = \begin{cases} 
\Theta^{(n)} \text{ with probability } \min\{1, \exp[\log L(\Theta^{(n)}) - \log L(\Psi^{(n)})]\} \\
\Psi^{(n)} \text{ otherwise}
\end{cases}
\]

The starting value \(\Psi^{(0)}\) is computed using maximum likelihood to estimate \(\{\text{chol}(\Omega_R), \text{chol}(\Omega_{NR})\}\) from the residuals of a second order approximation to equation (1) - (4) using lags of \(X_t, X_t z_t\), and \(X_t z_t^2\), and then estimating \(\{\Pi_R(L), \Pi_{NR}(L)\}\) using equation (8). The initial \(\Omega_{\psi}\) is chosen to be one percent of the parameter values and later adjusted on the fly for the first 10,000 draws to generate a 0.3 acceptance rates of candidate draws. I employ 50,000 draws and drop the first 10,000 draws.

I can construct the confidence intervals of the impulse responses using the generated chain of parameter values of \(\{\Psi^{(n)}\}_{n=1}^{N}\). The covariance of matrices are drawn following Auerbach and Gorodnichenko (2012) to avoid having near-zero entries in \(\text{chol}(\Omega_R)\) and \(\text{chol}(\Omega_{NR})\) that lead to wide confidence bands. I use 1,000 draws from \(\{\Psi^{(n)}\}_{n=1}^{N}\), and for each draw I compute an impulse response. The one-standard-deviation confidence bands are computed as the 16th and 84th percentiles of the generated impulse responses.
## Tables and Figures

### Table 1 Measurements of Uncertainty

<table>
<thead>
<tr>
<th>Variable</th>
<th>Summary Statistics</th>
<th>Correlation</th>
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<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>STD</td>
</tr>
<tr>
<td>JLN</td>
<td>0.683</td>
<td>0.102</td>
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<tr>
<td>VXO</td>
<td>19.710</td>
<td>7.319</td>
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<tr>
<td>StockVol</td>
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<tr>
<td>BBD</td>
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<td>45.424</td>
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<td>FDISP</td>
<td>0.686</td>
<td>0.091</td>
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**Table 2 Effect of Uncertainty Shocks**

<table>
<thead>
<tr>
<th></th>
<th>Normal</th>
<th>Recessions</th>
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<tbody>
<tr>
<td></td>
<td>w/ Conf</td>
<td>w/o Conf</td>
</tr>
<tr>
<td><strong>Panel A:</strong> Baseline, $X = [U, Conf, IP]'$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Impact</td>
<td>-0.402</td>
<td>-0.264</td>
</tr>
<tr>
<td>Max</td>
<td>-1.555</td>
<td>-1.138</td>
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<tr>
<td>Cumulative</td>
<td>-0.519</td>
<td>-0.249</td>
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<tr>
<td><strong>Panel B:</strong> Baseline, $X = [Conf, IP, U]'$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Impact</td>
<td>-0.000</td>
<td>0.000</td>
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<td>Max</td>
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<td>Cumulative</td>
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<tr>
<td><strong>Panel C:</strong> Baseline, $X = [IP, U, Conf]'$</td>
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<td></td>
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<tr>
<td>Impact</td>
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<td>0.000</td>
</tr>
<tr>
<td>Max</td>
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<td>-1.059</td>
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<tr>
<td>Cumulative</td>
<td>-0.476</td>
<td>-0.289</td>
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Figure 1 Uncertainty Indicators
Figure 2: Transition Probability $F(z)$ (12m MA) - Baseline

Figure 3: Effect of Uncertainty Shock: Linear vs. Recession
Figure 8 Robustness - StockVol as Uncertainty

Figure 9 Robustness - UMCSENT as Confidence
Figure 10 Robustness - X=[Conf, IP, U]

Figure 11 Robustness - X=[IP, U, Conf]
Figure 12 Transition Probability $F(z)$ (21m MA)

Figure 13 Robustness - 21 MA Transition Probability
Figure 14 Robustness - $X=[U, \text{Conf}, \text{IP}, \text{FFR}, \text{S&P500}]'$

Figure 15 Robustness - $X=[F1, F2, U, \text{Conf}, \text{IP}]'$