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THE ASYMMETRIC EFFECTS OF UNCERTAINTY ON MACROECONOMIC ACTIVITY

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We estimate a number of macroeconomic variables as logistic smooth transition autoregressive (LSTAR) processes with uncertainty as the transition variable. The notion is that the effects of increases in uncertainty should not be symmetrical with the effects of decreases in uncertainty. Nonlinear estimation allows us to answer several interesting questions left unanswered by a linear model. For a number of important macroeconomic variables, we show that (i) a positive shock to uncertainty has a greater effect than a negative shock and (ii) the effect of the uncertainty shock is highly dependent on the state of the economy. Hence, the usual linear estimates for the consequences of uncertainty are underestimated in circumstances such as the recent financial crisis.

Keywords: Nonlinear Models, STAR Models, Uncertainty Shocks, Logistic Uncertainty

1. INTRODUCTION

The large trough and subsequent slow recovery from the Great Recession of 2008–2009 has led to renewed discussion concerning the effect of uncertainty on the macroeconomy. For example, Becker et al. (2010) report, "According to the Michigan Survey of Consumers, 37 percent of households planned to postpone purchases because of uncertainty about jobs and income [. . . and] recent capital expenditures and near-term plans for new capital investments remain stuck at 35-year lows." Similarly, policy makers have emphasized the potential damaging effects of uncertainty. Consider the Federal Open Market Committee statement in April 2008: "Several [survey] participants reported that uncertainty about the economic outlook was leading firms to defer spending projects until prospects for economic activity became clearer."

Bernanke (1983) was one of the first to theorize that uncertainty shocks could cause recessions by incentivizing firms to delay investment and employment decisions during times of high uncertainty. More recently, Bloom (2009) and Bloom

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et al. (2012) developed simulation models in which positive uncertainty shocks lead to temporary reductions in investment and employment. Similarly, Gilchrist et al. (2014) suggest uncertainty shocks raise the cost of capital leading firms to reduce investment. Panousi and Papanikolaou (2011) find that an increase in uncertainty raises managerial risk aversion, and DeMarzo and Sannikov (2006) find that increases in uncertainty result in agency problems that reduce the value of employment. Finally, Baker et al. (2012) develop a policy-related uncertainty index and show that the increase in actual policy uncertainty between 2006 and 2011 could have led to as much as a 3.2% decline in GDP.

Unlike the aforementioned papers, we pursue Mishkin's (2011) suggestion that the effect of uncertainty on output is not likely to be linear, especially in the presence of a financial disruption. He argues that individuals tend to exaggerate the effects of worst-case scenarios and appear to be more risk-averse in downturns than in upturns. Moreover, as in Eisner and Strotz (1963), Lucas and Prescott (1971), Lucas (1981), and Bloom (2009), investment and employment decisions for an individual firm depend on adjustment costs. Relatively small changes in the level of uncertainty may not induce changes in the firm's desired capital stock. However, in the face of a relatively large change in the level of uncertainty, firms are likely to alter their investment decisions as the costs of adjustment become small relative to the costs of inaction. Finally, it takes longer to expand capacity and hire labor than it takes to shut down capacity or lay off workers.[1] Thus, we anticipate that uncertainty increases have larger and more persistent effects than uncertainty decreases. The issue is important, because the aforementioned linear measures of the consequences of uncertainty are essentially averages across different states of the economy. We show that the macroeconomic consequences of uncertainty are especially large when uncertainty is already widespread, as in the aftermath of the Great Recession.

We estimate the effects of uncertainty on key macroeconomic variables using a nonlinear framework that allows the sign and magnitude of the uncertainty shocks to have asymmetric effects.[2] Although the theory of the firm allowing for a fixed cost of adjustment indicates that investment acts as a threshold process, aggregating across all firms in the macroeconomy suggests that the region of inaction is actually a smooth process. To capture this type of behavior, we employ an LSTAR model consisting of a high-uncertainty and a low-uncertainty regime with a smooth transition between the two. We use our LSTAR model to examine the differential effects of positive and negative uncertainty shocks both before and during the recent financial crisis. Our LSTAR model can produce impulse response functions that answer three important questions: do positive and negative uncertainty shocks have asymmetric effects, do the effects of uncertainty shocks vary over the business cycle, and do the effects of uncertainty shocks vary disproportionately with the size of the shock?

In Section 2, we describe the data, present linear estimates of important macroeconomic variables, and pretest the data for nonlinearities. Section 3 presents our combination of an exponential generalized autoregressive conditional heteroskedastic (EGARCH) model with an LSTAR model in order to capture the types of nonlinearities likely to exist in the data. Section 4 looks at historical decompositions, and Section 5 evaluates the asymmetric effects of uncertainty shocks on output both before and during the recent financial crisis using generalized impulse response functions. Our results show a positive shock to uncertainty is more persistent and has a greater effect than a negative shock to uncertainty. Also, the effect of the uncertainty shock is highly dependent on whether the shock occurs before or during the crisis. In Section 6, we show that the LSTAR specification also captures the responses of a number of other important macroeconomic variables to a number of different measures of uncertainty. Specifically, industrial production, durable goods, employment, consumer credit, bank loans, and bank cash all display a greater response to positive uncertainty shocks than to negative uncertainty shocks. It is interesting that all but one of these variables decline in response to increases in uncertainty whereas banks increase their cash holdings as uncertainty rises. Section 7 concludes.

2. DATA AND PRETESTING FOR NONLINEARITY

2.1. Data

There is no consensus on the best measure of uncertainty, so our approach is to use different measures that have appeared in the academic literature. In Section 3, we follow Bloom (2009) and use the variance of the S&P 500 as our measure of uncertainty.[3] In Section 6, we use several alternative uncertainty measures. Bloom's (2009) primary uncertainty measure is an indicator function that equals unity for seventeen important shocks and zero otherwise. Specifically, these seventeen shocks are events when the Hodrick–Prescott (HP) detrended volatility of the S&P 500 index rises 1.65 standard deviations above its mean.[4] In a sense, this methodology allows only the large positive-uncertainty shocks to have macroeconomic consequences. Instead, we estimate the S&P 500 index as a GARCH process and use the estimated conditional variance as our uncertainty measure.[5] This allows all uncertainty shocks (regardless of sign and magnitude) to affect the macroeconomy. We also depart from using Bloom's (2009) measure of output. He defines output as the HP detrended log of monthly industrial production.[6] Instead, to avoid any controversy involved with the use of the HP filter, our output measure is the log difference of monthly industrial production.[7] Our data series and transformations are further described in the Appendix.

2.2. Characteristics of an LSTAR Model

Because much of the following econometric analysis is carried out using the LSTAR model, this subsection explains the basic LSTAR model and its characteristics. Consider the following LSTAR model presented in van Dijk et al. (2002):

$$y_t = \phi_1' x_t \left[1 - G\left(s_t; \gamma, c\right)\right] + \phi_2' x_t G\left(s_t; \gamma, c\right) + \varepsilon_t, \qquad (1)$$

where $x_t = (1, \tilde{x}_t')'$ with $\tilde{x}_t = (y_{t-1}, ..., y_{t-p})'$, and $\phi_i = (\phi_{i,0}, \phi_{i,1}, ..., \phi_{i,d})'$, $i = 1, 2$. The error term ε_t is assumed to be a martingale difference sequence with respect to the information set Ω_t such that $E[\varepsilon_t|\Omega_{t-1}] = 0$, where $\Omega_{t-1} = \{y_{t-1}, y_{t-2}, \ldots, y_{1-p}\}$. The conditional variance of ε_t is assumed to be constant, $E[\varepsilon_t^2|\Omega_{t-1}] = \sigma^2$, and the transition function $G(s_t; \gamma, c)$ is a first-order logistic function such that

$$G(s_t; \gamma, c) = (1 + \exp[-\gamma (s_t - c)])^{-1}, \gamma > 0, \quad \mathbf{(2)}$$

where s_t is the transition variable, γ is the smoothness parameter, c is the centrality parameter, and $G(s_t; \gamma, c)$ is a continuous function bounded between 0 and 1.

The LSTAR model can be thought of as a regime-switching model with two regimes that allows a smooth transition between the two regimes. The regime is controlled by the transition variable s_t and the associated value of $G(s_t; \gamma, c)$. The smoothness parameter γ determines the smoothness of the transition between the two regimes, and the centrality parameter c is the threshold between the two regimes. $G(s_t; \gamma, c)$ changes monotonically from 0 to 1 as s_t increases and is equal to 0.5 when $s_t = c$. When $\gamma \to 0$, $G(s_t; \gamma, c)$ approaches 0.5 and at $\gamma = 0$, the LSTAR model reduces to a linear autoregressive model. The LSTAR model also nests a two-regime threshold autoregressive (TAR) model. As γ becomes very large, the change of $G(s_t; \gamma, c)$ from 0 to 1 becomes instantaneous at the centrality parameter c. Because the LSTAR model nests a linear model as well as a TAR model, it can be a convenient tool for modeling various business cycle variables.

2.3. Pretesting for Nonlinearity

Before we estimate each series as a nonlinear process, it seems reasonable to pretest for nonlinearity in order to determine whether each series displays some sort of nonlinear adjustment. To this end, we subject each series to a battery of tests for nonlinearity. Note that these tests can only suggest whether or not the data generating process is nonlinear and may not be able to pinpoint the proper form of nonlinearity. We employ the following diagnostic tests for nonlinearity:

Pretesting for STAR models. Teräsvirta (1994) creates a framework to detect the presence of nonlinear behavior using a Taylor series expansion of the general STAR model. This is necessary because it is not possible to perform a Lagrange multiplier (LM) test for the presence of STAR behavior directly. The null hypothesis in an LM test for nonlinearity (i.e., $\gamma = 0$) suffers from the so-called Davies problem because ϕ_1, ϕ_2, and c are unidentified under the null of $\gamma = 0$. Instead, Teräsvirta (1994) approximates the transition function, $G(s_t; \gamma, c)$, with a Taylor series approximation around $\gamma = 0$. The reparameterized equation no longer suffers from this identification problem and linearity can be tested by an LM statistic with an asymptotic χ^2 distribution under the null hypothesis. The

LSTAR model

$$y_t = \phi_1' x_t + (\phi_2 - \phi_1)' x_t G(s_t; \gamma, c) + \varepsilon_t \qquad \textbf{(3)}$$

combines (1) and (2) and assumes that $\{\varepsilon_t\} \sim$ n.i.d.$(0, \sigma^2)$. Approximating the logistic function $G(s_t; \gamma, c)$ with a third-order Taylor series approximation around $\gamma = 0$ results in the auxiliary regression

$$y_t = \beta_0' x_t + \beta_1' x_t s_t + \beta_2' x_t s_t^2 + \beta_3' x_t s_t^3 + e_t, \qquad \textbf{(4)}$$

where $e_t = \varepsilon_t + (\phi_2 - \phi_1)' x_t R_3(s_t; \gamma, c)$, with $R_3(s_t; \gamma, c)$ the remainder term from the Taylor expansion. The β_is are functions of the parameters ϕ_1, ϕ_2, γ, and c, and the null hypothesis $H_0' : \gamma = 0$ corresponds to $H_0'' : \beta_1 = \beta_2 = \beta_3 = 0$. The LM test statistic has an asymptotic χ^2 distribution with $3(p+1)$ degrees of freedom.[8]

Regression error specification test (RESET). The regression error specification test cannot determine the specific form of nonlinearity but assumes the null hypothesis of linearity against a general alternative of nonlinearity. The residuals from a true linear model should not be correlated with the regressors used in the estimating equation or powers of the fitted values. Therefore, a regression of the residuals on powers, the fitted values, and the regressors should have little explanatory power if the model is linear.

Testing for threshold effects. Hansen (1997) develops a supremum test to check for threshold effects and shows how to obtain the appropriate critical values using a bootstrapping procedure. The procedure searches over all possible thresholds to find the best-fitting threshold model. If the F value exceeds the critical value from the bootstrapped F distribution, the null hypothesis of linearity is rejected.

2.4. Nonlinear Test Results

The top portion of Table 1 reports the results from the three nonlinear tests for each of the macroeconomic variables used in our study.[9] For Teräsvirta's (1994) test the transition variable s_t in (3) is assumed to be a lagged endogenous variable, i.e., $s_t = y_{t-1}$. As shown in the table, when we apply Teräsvirta's (1994) test to industrial production, we obtain an F-statistic of 2.52, which is significant at the 5% significance level. Notice that each variable has at least two tests that allow us to reject the null hypothesis of linearity at the 10% significance level. This suggests that nonlinear models are likely to capture the time series dynamics of these macroeconomic variables better than linear models. However, the particular form of nonlinearity cannot be pinned down by the nonlinear tests. Section 3 discusses our particular nonlinear framework.

TABLE 1. Nonlinearity tests

Nonlinear test[a]	Industrial production	Durable goods	Employment	Consumer credit	Bank loans	Bank cash
Teräsvirta (1994)	2.52^{**}	18.72^{***}	6.30^{***}	0.85	2.93^{***}	8.56^{***}
RESET	2.15^{*}	18.72^{***}	0.91	2.08^{*}	3.37^{**}	14.09^{***}
Threshold effect	2.75	20.32^{***}	12.53^{***}	12.03^{***}	4.38^{***}	5.18^{***}
	Sign bias test	Negative sign bias test	Positive sign bias test	All three tests		
Engle and Ng (1993)	4.22^{***}	-2.10^{**}	-3.93^{***}	20.09^{***}		

[a] Under the null hypothesis, each process is linear.
*,**,*** 10%, 5%, and 1% significance levels.

2.5. Testing for EGARCH Behavior in Uncertainty

Given that our macroeconomic variables should be modeled using a nonlinear framework, we proceed to test whether our uncertainty measure is also nonlinear. Engle and Ng (1993) develop a way to determine if positive and negative shocks have different effects on the conditional variance of a series. Let the model of the S&P 500 have the simple form

$$\Delta \ln(x_t) = a + \varepsilon_{1t}, \tag{5}$$

where $\Delta\ln(x_t)$ is the log difference of the S&P 500, a is a constant, $\varepsilon_{1t} \sim N(0, h_t)$ conditional on the information available up to time $t-1$, and h_t is a GARCH(1,1) process such that the standardized residuals $\{v_t\}$ can be written as

$$v_t = \varepsilon_{1t}/\sqrt{\hat{h}_t}.$$

Let D^-_{t-1} be a dummy variable equal to 1 if $v_{t-1} < 0$ and equal to zero if $v_{t-1} \geq 0$. The sign bias test from Engle and Ng (1993) determines if the $\{D^-_{t-1}\}$ sequence can predict the estimated squared residuals. Not only can the sign of the shock affect the conditional variance asymmetrically, but also the size or magnitude of a shock can be asymmetric. To test for asymmetric size effects, we conduct a negative (positive) size bias test by regressing the estimated squared residuals on v_{t-1} times D^-_{t-1} (D^+_{t-1}).

The lower part of Table 1 reports the results of Engle and Ng's (1993) tests for asymmetry. The simple GARCH(1,1) model is given by $h_t = 0.00009 + 0.01\varepsilon^2_{t-1} + 0.84h_{t-1}$. We use the standardized residuals from this model to conduct the tests for asymmetry. A significant coefficient from the sign bias test indicates that positive and negative shocks have different impacts on the conditional variance. Moreover, coefficients from the positive and negative size bias tests are all significant at conventional levels. The χ^2 test for the combination of all three tests provides additional evidence supporting the use of an asymmetric EGARCH model. The Akaike information criterion (AIC) and the Bayesian information criterion (BIC) from the EGARCH model are also smaller than those from the simple GARCH(1,1) model. Therefore, we estimate the following EGARCH(1,1) model as our measure of uncertainty (with t-statistics in parentheses):

$$\begin{aligned} \log h_t = \underset{(-3.02)}{-0.82} + \underset{(3.48)}{0.21} \left|\varepsilon_{1t-1}\right| / \sqrt{h_{t-1}} + \underset{(23.15)}{0.90}\log h_{t-1} - \underset{(-4.21)}{0.11}\varepsilon_{1t-1}/\sqrt{h_{t-1}}. \end{aligned} \tag{6}$$

The key feature of (6) is the negative coefficient on $\varepsilon_{1t-1}/\sqrt{h_{t-1}}$, which guarantees that negative shocks will produce higher variances than similarly sized positive shocks. Panel A of Figure 1 shows the estimated conditional variance of the S&P 500 index obtained from equation (6) along with monthly U.S. industrial production. Recessions, as defined by the NBER, are represented by shaded areas in Figure 1. Although it does appear that positive increases in uncertainty often accompany decreases in output, this is not always the case. The most obvious

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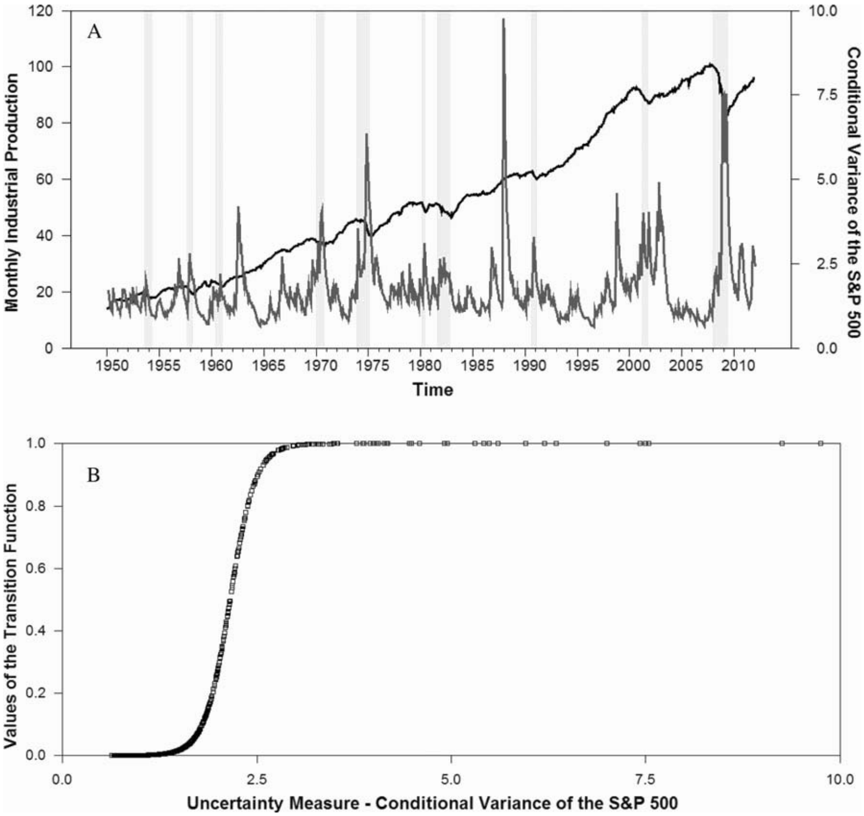

FIGURE 1. Uncertainty and industrial production. (A) Conditional variance of the S&P 500 along with monthly U.S. industrial production; (B) values of the transition function in the LSTAR model. Panel A shows the conditional variance estimated by an EGARCH(1,1) model normalized by dividing by the standard deviation of the series, along with monthly industrial production.

example is the lack of a significant drop in output following the increase in uncertainty associated with Black Monday, October 19, 1987. This suggests that the effects of an uncertainty shock may depend on the current state of the business cycle at the time of the uncertainty shock.

2.6. Testing Our Specific Model

The final pretest involves changing the transition variable s_t in (3). In Section 3, we model industrial production as an LSTAR process with our measure of uncertainty, h_t, as the transition variable. In this way, we test the null hypothesis of linearity directly against the alternative of an LSTAR model with h_t as the transition variable. After carrying out this procedure, we obtain an F-statistic of

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3.92, which is significant at the 1% level. Thus, we reject the null hypothesis of linearity and accept the alternative nonlinear model discussed more fully in Section 3.

3. THE NONLINEAR MODEL OF INDUSTRIAL PRODUCTION

In this section, we follow Bloom (2009) and focus on the effect of uncertainty on industrial production. The other important macroeconomic variables listed in Table 1 are analyzed in Section 6. To begin with, we compare a linear model of the industrial production series with our nonlinear specification. For the linear model, the BIC selects a model with two lags.[10] Let y_t denote the logarithmic change in monthly industrial production, so that

$$\begin{aligned} y_t &= \underset{(3.91)}{0.0013} + \underset{(9.88)}{0.36}y_{t-1} + \underset{(3.27)}{0.12}y_{t-2} + \varepsilon_{2t} \\ \text{AIC} &= -2129.1 \ \text{BIC} = -2115.3, \end{aligned} \tag{7}$$

where ε_{2t} denotes the error term for the $\{y_t\}$ process.

The Ljung–Box Q-statistics indicate that the residuals are serially uncorrelated. For example, the Q-statistics using the first four and eight lags of the standardized residual autocorrelations have prob-values of 0.21 and 0.25, respectively. The linear model represented by (7) indicates that the $\{y_t\}$ series is not especially persistent; the two characteristic roots are approximately -0.21 and 0.57. More importantly, the model implies that adjustment is symmetric, in the sense that mean reversion is invariant in the sign and magnitude of the discrepancy of y_t from its mean. Hence, linearity implies that the phase of the business cycle is irrelevant.

The preceding estimation of a linear model allows us to compare the characteristics of the linear model of industrial production with our LSTAR specification. The two models can also be compared based on the AIC and BIC. To allow uncertainty shocks to have differential effects on industrial production, we estimate the $\{y_t\}$ series as an LSTAR process. The central feature of the LSTAR specification is the ability to model high- and low-uncertainty regimes with a smooth transition between the two. Moreover, the LSTAR model nests a threshold process; if, in equation (3), γ is sufficiently large, the LSTAR and threshold specifications are essentially identical. Consider the following LSTAR model of industrial production, written in the form of (3):[11,12]

$$\begin{aligned} y_t &= \underset{(7.13)}{0.003} + \underset{(8.26)}{0.28}y_{t-1} + (\underset{(-5.97)}{-0.005} + \underset{(5.61)}{0.35}y_{t-1})[1 + \exp(-6.146\,(h_t - 2.155))]^{-1} + \varepsilon_t, \\ \text{AIC} &= -2145.7 \quad \text{BIC} = -2118.1, \end{aligned} \tag{8}$$

where y_t denotes the fitted values of the $\{y_t\}$ process.

Notice that the transition variable in (8) is the contemporaneous value of uncertainty from (6) as opposed to the lagged value of industrial production. Also

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note that the AIC and BIC from the LSTAR model are both smaller than the AIC and BIC from the linear model, even though the LSTAR model estimates three additional parameters. Panel B of Figure 1 shows the values of the transition function plotted as a function of h_t. In comparing the two panels of Figure 1, note that $c = 2.155$ is close to the center of the estimated h_t series and that the transition between regimes is reasonably sharp.

If you examine the skeleton of equation (8), it should be clear that when the transition function equals zero (i.e., when uncertainty is low), the long-run equilibrium of output growth is positive, and the coefficient on y_{t-1} is equal to 0.28. However, when the transition function equals one (i.e., uncertainty is high), the long-run equilibrium of output growth is negative, and the coefficient on y_{t-1} is 0.63 (i.e., $0.28 + 0.35 = 0.63$). Therefore, high values of uncertainty decrease output and are more persistent than low values of uncertainty.

4. HISTORICAL DECOMPOSITIONS

To highlight the effects of uncertainty on output, we perform two counterfactual analyses; one for the 2000:M1−2012:M1 period and the other for the 2009:M6−2012:M1 period. For the 2000:M1–2012:M1 period, we fix the value of uncertainty to the average value over the 1990s. Therefore, the h_t series is set equal to 1.48, and the transition function is equal to approximately zero for each time period. Then we set the initial condition for y_t equal to the actual value of industrial production growth for 2000:M1 and iterate forward. Panel A of Figure 2 shows the recursive counterfactual values of industrial production compared to the actual values.[13] Clearly, if the uncertainty values for the 1990s had continued, we would have expected strong output growth. Specifically, the level of industrial production at the end of the twelve-year period is estimated to be almost 70% higher than the actual value.

Panel B of Figure 2 shows the time series plot of actual and counterfactual industrial production for the second historical decomposition, 2009:M6–2012:M1. For this decomposition we set h_t equal to the average value of uncertainty during the recent financial crisis (i.e., h_t is fixed at 4.98, so that the transition function is approximately one). Then we set the initial condition y_t equal to the actual value for 2009:M6 and iterate forward. As shown in the figure, if the uncertainty level had remained constant at its average level for the financial crisis, output would have continued to decline sharply. Note that over the 2009:M6–2012:M1 period, counterfactual industrial production would have fallen by more than 20% as compared to the actual value.

5. IMPULSE RESPONSE FUNCTIONS

Koop et al. (1996) develop a framework for estimating impulse responses from nonlinear models. Traditional impulse response functions have a symmetry property (e.g., a shock of -1 has exactly the opposite effect of a shock of $+1$) and a

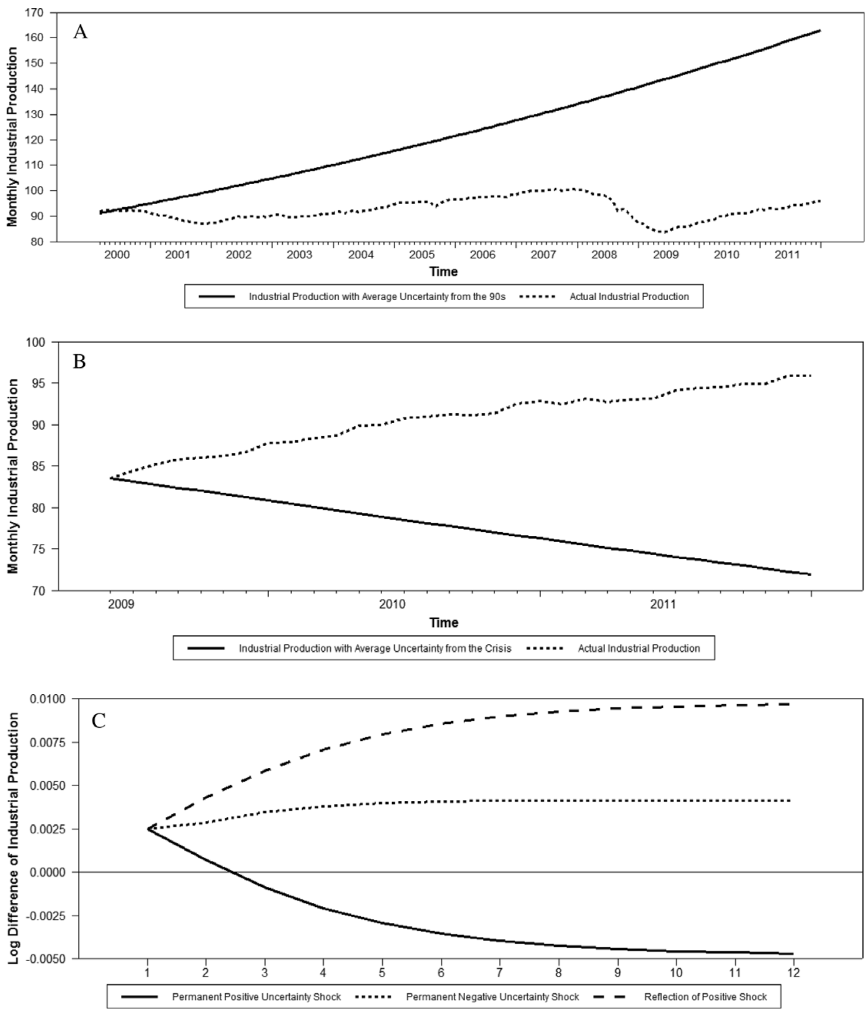

FIGURE 2. Historical decompositions and continuing uncertainty shocks. (A) Decomposition if uncertainty equals its average value during the 1990s; (B) decomposition if uncertainty equals its average value during the financial crisis; (C) effects of continuing shocks to uncertainty. Panel C shows the asymmetric effects of a continuing positive and a continuing negative uncertainty shock. The reflection of the positive shock shows that positive shocks have greater effects than negative shocks.

linearity property (e.g., a shock of size 2 has exactly twice the effect of a shock of size 1). However, the interpretation of impulse response functions for a nonlinear model is not as straightforward because the initial state of the system, as well as the size, sign, and subsequent values of the shocks, affects the responses.

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To calculate generalized impulse responses, we specify the history of the system and the value of the uncertainty shock. Then we select randomly drawn realizations of the residuals from (5) to produce $\varepsilon^*_{1t+1}, \varepsilon^*_{1t+2}, ..., \varepsilon^*_{1t+24}$. Because the residuals may not have a normal distribution, we select the residuals using standard bootstrapping procedures. In particular, we draw the residuals from a uniform distribution with replacement and use them to produce $\{h^*_t\} = h^*_t$ through h^*_{t+24}. These $\{h^*_t\}$ values are substituted into the LSTAR model given by (8) to generate the recursive values of y^*_t through y^*_{t+24}. For each particular history, we repeat the process 1,000 times and obtain the mean values of the impulse responses, along with the 95% confidence intervals.

5.1. Impulse Response Results

Panel C of Figure 2 shows the impulse responses of continuing positive and negative uncertainty shocks on output. We initialize the model in period one by setting the magnitude of uncertainty equal to the centrality parameter c and the log difference of industrial production equal to the equilibrium suggested from the linear model. Thus, the transition function equals $^1/_2$ in period one before the uncertainty shocks, and industrial production is equal to 0.0013/(1 - 0.36 - 0.12) = 0.0025. Note that with the parameterization of the EGARCH model, a negative innovation in the residuals leads to a higher conditional variance and is a positive uncertainty shock.

Because we want to focus on the effects of uncertainty shocks on output, we take an alternative approach to that discussed in Koop et al. (1996). Instead of drawing random shocks for the output sequence, we consider the effects of shocks to the uncertainty sequence. Specifically, the uncertainty shocks in Panel C of Figure 2 are continuing positive and negative one-standard-deviation shocks from the residuals of (5). Hence, for a continuing positive (negative) uncertainty shock, the value of uncertainty in every period is determined by setting the residuals $\varepsilon^*_{1t+1}, \varepsilon^*_{1t+2}, \ldots, \varepsilon^*_{1t+12}$ equal to a minus (plus)-one-standard-deviation innovation. As shown by the reflection of the continuing positive uncertainty shock in Panel C of Figure 2, increases in uncertainty have larger effects on output than decreases in uncertainty. Specifically, industrial production falls from 0.0025 to −0.0054 for the continuing positive uncertainty shock and rises only from 0.0025 to 0.00417 for the continuing negative uncertainty shock.[14] Also, consistent with our historical decompositions, continuing high values of uncertainty lead to large decreases in output, and continuing low values of uncertainty lead to large increases in output.

Panel A of Figure 3 shows the effects of a temporary positive one-standard-deviation shock to uncertainty during the recent financial crisis. Unlike the procedures used to produce Figure 2, here we change only the value of ε^*_{1t} for 2008:12 and select the subsequent residuals using standard bootstrapping procedures. We repeat this procedure 1,000 times. The figure shows the mean values of industrial production, along with 95% confidence intervals. Initially, a positive

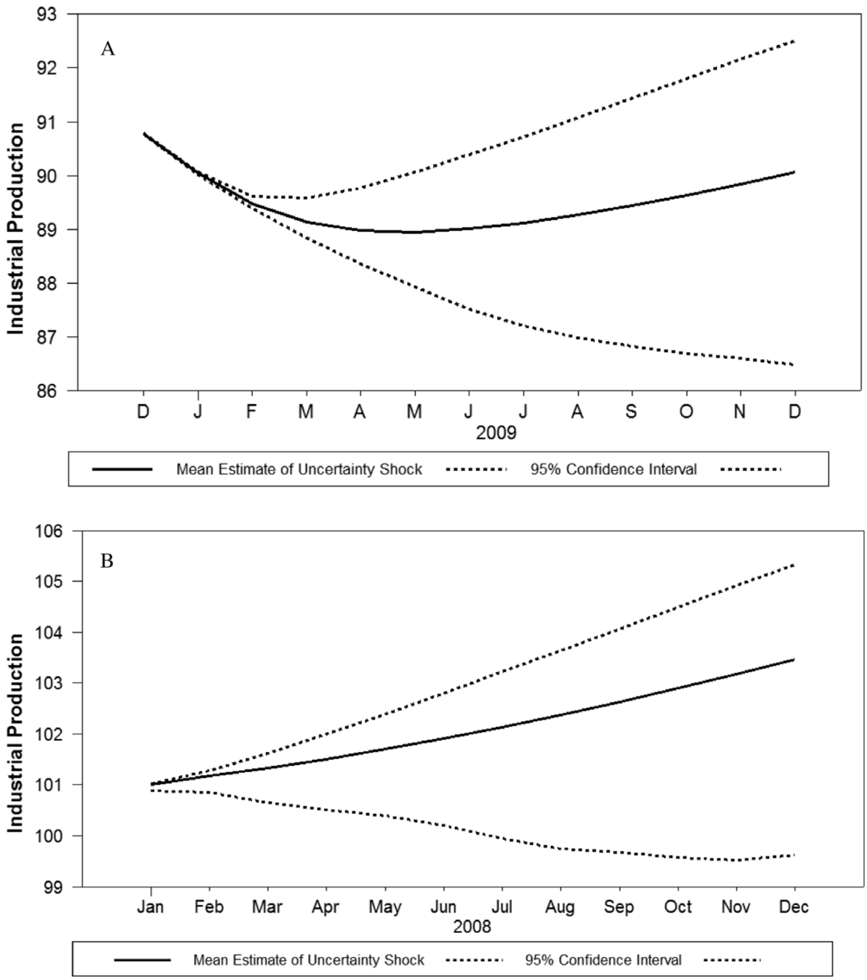

FIGURE 3. Impulse responses to a temporary positive uncertainty shock. (A) Impulse response to a positive one-standard-deviation uncertainty shock occurring in 2008:12; (B) impulse response to a 2008:12 uncertainty shock occurring in 2008:1.

one-standard-deviation uncertainty shock causes industrial production to fall. The series returns to its original value in little more than a year.

Panel B of Figure 3 shows how an actual uncertainty shock from the midst of the financial crisis (2008:12) would have affected output if it had occurred in 2008:1 (i.e., before the onset of the crisis). The actual magnitude of the shock is more than twice that used in Panel A of Figure 3. Nevertheless, the effect of the shock on output is small; output continues to rise in spite of the shock. Although the 2008:12 uncertainty shock actually had a large negative effect on output for that period, our counterfactual analysis shows that it would have had little effect if it had occurred

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when the economy was strong. The key point is that this hypothetical increase in uncertainty occurs when the state of the economy is strong. Therefore, uncertainty shocks occurring during deep recessions such as the recent financial crisis have vastly different effects than the same-sized shocks occurring during expansions.

One interesting feature of the LSTAR model is that the consequences of the uncertainty shocks need not be homogeneous of degree one in the size of the shock. In Panel A of Figure 4, we investigate how different-sized shocks would affect industrial production were they all to occur in 2008:12. The solid, dotted, and dashed lines show bootstrapped mean values of +2, +1, and −1 standard deviation temporary shocks on industrial production, respectively. Notice that the uncertainty shocks affect industrial production negatively in each case, even when the shock is negative. However, positive uncertainty shocks lead to larger decreases in output and longer recovery times than negative uncertainty shocks. Following a negative one-standard-deviation uncertainty shock, output returns to preshock levels after approximately 12 months. After a positive one-standard-deviation shock, output recovers after approximately 18 months, and after a positive two-standard-deviation shock, output returns to preshock levels in approximately 24 months.

Panel B of Figure 4 shows the results of repeating the exercise assuming that the same-sized shocks occurred on 2008:1. In this case, the temporary uncertainty shocks barely affect output. Even large positive uncertainty shocks do not affect output substantially. The point is that reasonable-sized uncertainty shocks—even as much as two standard deviations—occurring during a favorable state of economic activity have little effect.

5.2. An Alternative Methodology

Throughout the preceding analysis we assume that increases in uncertainty cause output to drop, but it could be possible that the drop in output causes the increase in uncertainty. Therefore, an alternative methodology estimates the growth rate of industrial production and uncertainty as a simultaneous system to test for causality. In this section, we use the volatility based on the Chicago Board of Options Exchange VXO index as our measure of uncertainty.[15] Using this methodology, we are able to shed light on the following question of causality: Does an increase in uncertainty cause output to drop or does a decrease in output cause uncertainty to increase? We continue to estimate y_t as an LSTAR process and estimate the VXO as an equation in a vector autoregression (VAR). Consider the following estimation:

$$\begin{aligned}
y_t &= \underset{(6.93)}{0.0033} - \underset{(-1.80)}{0.15}y_{t-1} + (\underset{(-5.20)}{-0.0039} + \underset{(6.62)}{0.76}y_{t-1})] \\
&\quad \times [1 + \exp(-4.36\,(vxo_{t-1} - 23.23))]^{-1} + \varepsilon_{3t}. \\
vxo_t &= \underset{(4.54)}{3.55} + \underset{(25.24)}{0.83}vxo_{t-1} + \underset{(0.70)}{30.45}y_{t-1} + \varepsilon_{4t}.
\end{aligned}$$

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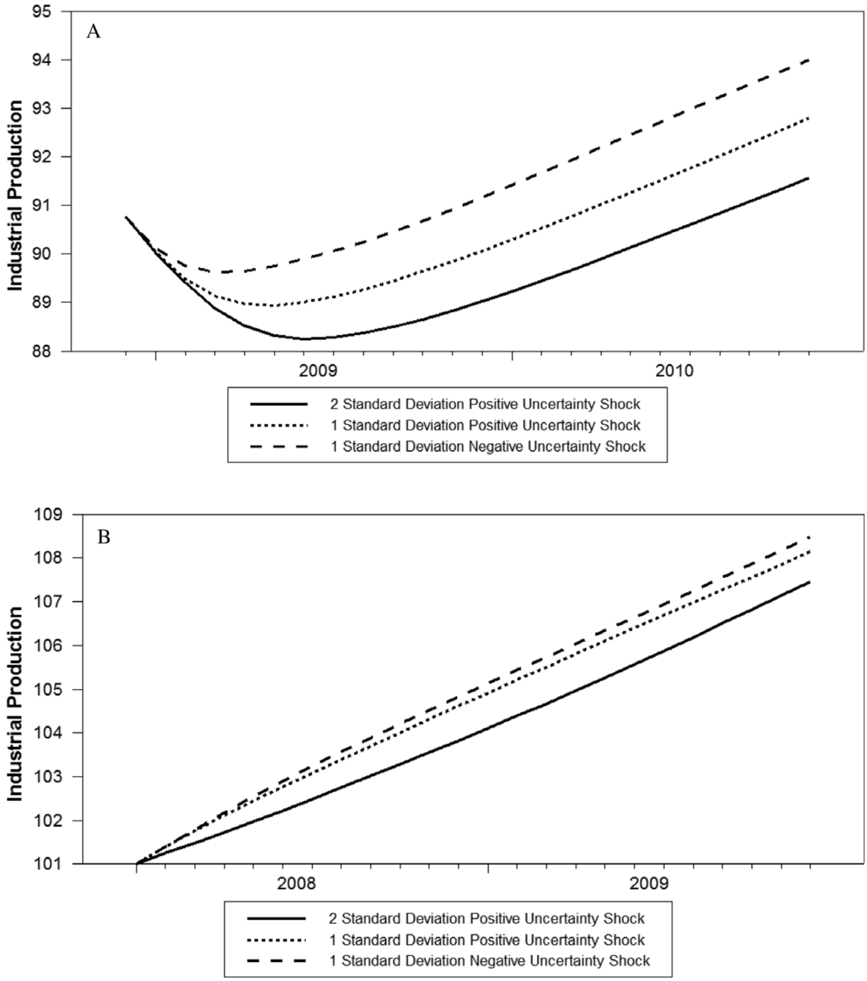

FIGURE 4. The asymmetric effects of temporary uncertainty shocks. (A) Impulse responses to uncertainty shocks during the financial crisis (2008:12); (B) impulse responses to uncertainty shocks before the financial crisis (2008:1). The figure shows the impulse responses to a temporary positive one-standard-deviation uncertainty shock, a temporary positive two-standard-deviation uncertainty shock, and a temporary negative one-standard-deviation uncertainty shock before and during the financial crisis. All lines show mean estimates of each impulse response.

All of the estimates in the nonlinear system are obtained simultaneously using nonlinear least squares. Once again, the transition variable in the LSTAR model of output is the lagged value of the VXO index as opposed to lagged values of output. Notice in the equation for uncertainty that the coefficient on output is insignificant. In a sense, the *t*-statistic in this case acts like a Granger causality test. Thus, an

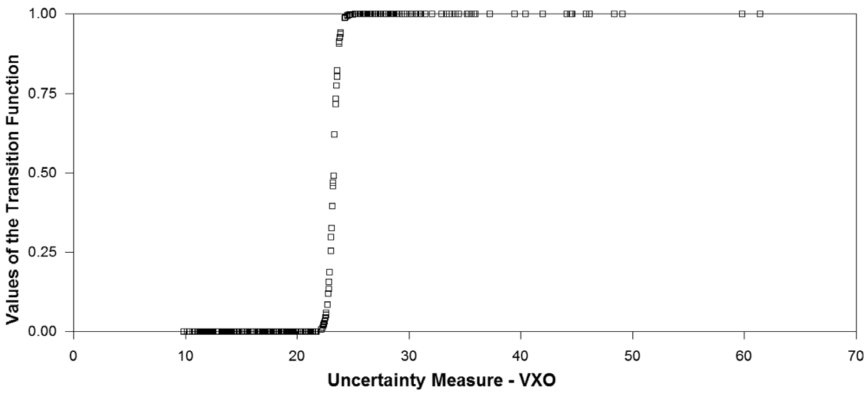

FIGURE 5. Values of the transition function in the nonlinear VAR model. The uncertainty measure in the nonlinear VAR is the implied volatility based on the Chicago Board of Options Exchange VXO index.

insignificant coefficient suggests that output is not driving uncertainty, but in fact changes in uncertainty are causing changes in output.

Figure 5 plots the values of the transition function against our uncertainty measure. When the transition function is zero and uncertainty is low, the long-run equilibrium of output is positive, and the coefficient on y_{t-1} is equal to -0.15. However, when the transition function equals one and uncertainty is high, the long-run equilibrium of output is negative, and the coefficient on y_{t-1} is 0.61. Therefore, consistent with our previous estimation, high values of uncertainty decrease output and are more persistent than low values of uncertainty.

6. ALTERNATIVE MEASURES OF UNCERTAINTY AND OTHER IMPORTANT MACROECONOMIC VARIABLES

To determine whether uncertainty shocks induce asymmetric responses in other sectors, we investigate the effects of uncertainty on a number of other important macroeconomic variables. Moreover, to ensure that the results are robust, we examine the effects of several uncertainty measures. The results are presented in Table 2. In each case, uncertainty is the transition variable in the most appropriate LSTAR model for each sector, and β_0 is a measure of the effect of high values of uncertainty on each of the macroeconomic variables. Interestingly, all of the coefficient estimates of β_0 are negative except for the last regression. This means that high values of uncertainty cause a drop in every important macroeconomic variable except bank cash, which increases during times of high uncertainty. In other words, an increase in uncertainty decreases production and financial flows, but increases the amount of cash that banks choose to hold. This also provides evidence for the direction of causality between uncertainty and output. If the

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TABLE 2. Alternate measures of uncertainty in important macroeconomic variables:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + (\beta_0 + \beta_1 y_{t-1})[1 + \exp(-\gamma(u_t - c))]^{-1} + \varepsilon_t$$

	S&P 500 variance			BOS data			Uncertainty index			Interest rate spread
	Industrial production	Consumer credit	Employment	Industrial production	Durable goods	Consumer credit	Industrial production	Bank loans	Consumer credit	Bank cash
α_0	0.003***	0.0031***	0.0016***	0.003***	0.008***	0.0059***	0.003***	0.0005	0.002***	0.004**
	(0.00048)	(0.0006)	(0.00013)	(0.00061)	(0.0029)	(0.00091)	(0.00045)	(0.00047)	(0.00033)	(0.002)
α_1	0.28***	0.61***	0.25***	0.31***	0.08	0.195*	–0.07	0.74***	0.62***	–0.007
	(0.045)	(0.042)	(0.039)	(0.060)	(0.072)	(0.11)	(0.079)	(0.053)	(0.047)	(0.055)
β_0	–0.005***	–0.0026**	–0.0016***	–0.004**	–0.028	–0.0044***	–0.003***	–0.0009	–0.0016**	0.04*
	(0.0011)	(0.001)	(0.0002)	(0.0015)	(0.028)	(0.00095)	(0.00078)	(0.0015)	(0.00072)	(0.02)
β_1	0.35***	0.08	0.55***	0.03	–0.15	0.53***	0.45***	–0.20	–0.0034	0.62***
	(0.102)	(0.11)	(0.067)	(0.10)	(0.28)	(0.11)	(0.11)	(0.11)	(0.16)	(0.096)
γ^a	5889	3097	606899	38.6	14.6	2620	13.04	9.15	8.22	8.17
	(4197)	(2892)	(289075)	(33.9)	(12.1)	(2933)	(83.8)	(2219)	(74266)	(39)
c^b	0.00225	0.0022	0.0018	0.736	0.8	0.515	115	161	152	3.96
	(0.00014)	(0.00032)	(0.0001)	(0.028)	(0.13)	(0.001)	(0.51)	(66.8)	(658)	(0.75)

Note: The table reports estimates for each parameter in the LSTAR model for different uncertainty measures, u_t. Standard errors are in parentheses.
[a]The parameters are undefined when $\gamma = 0$. Therefore, significance levels for the null hypothesis $\gamma = 0$ are not reported.
[b]Significance levels for $c = 0$ are not reported because our uncertainty variables are always positive.
*,**,*** 10%, 5%, and 1% significance levels.

change in output were causing uncertainty to change, it is unlikely that uncertainty would affect each production and financial flow variable similarly.

Because the value of β_1 can also affect the long-run equilibrium, Table 3 examines the skeleton of each model to determine the long-run equilibrium for each regime. The high-uncertainty regime equilibrium is calculated by setting the transition function equal to one and the low-uncertainty regime equilibrium is found by setting the transition function equal to zero in each of the LSTAR models reported in Table 2. For example, the last column of Table 2 reports estimates for the LSTAR model of bank cash with the spread between the 30-year corporate junk bond and the 30-year Treasury bond as the measure of uncertainty. When the transition function equals one, the sum of the intercept terms equals $0.004 + 0.04 = 0.044$, and the sum of the autoregressive coefficients equals $-0.007 + 0.62 = 0.613$. Therefore, the high-uncertainty regime equilibrium is $0.044/(1 - 0.613) = 0.1137$. The difference between the high-uncertainty regime equilibrium and the equilibrium suggested by the linear model is $0.1137 - 0.00632 = 0.10738$. Notice that the absolute values of the difference between the high-uncertainty regime equilibrium and the equilibrium suggested from the linear model are greater than the differences between the low-uncertainty regime equilibrium and the equilibrium suggested by the linear model in every case except one. The exception is when our uncertainty measure is Business Outlook Survey (BOS) data and our macroeconomic variable is consumer credit. Often the effects of positive uncertainty shocks are several times larger than negative uncertainty shocks.[16] Therefore, we conclude that positive uncertainty shocks have larger effects than negative uncertainty shocks across a number of important macroeconomic variables and various measures of uncertainty.

6.1. The Asymmetric Effects of Uncertainty on Consumer Credit

Given the recent claims that banks have been hoarding cash and frustrating the Federal Reserve's efforts to stimulate the economy, we examine the effects of uncertainty shocks on consumer credit in more detail. Specifically, we look at how the conditional variance of the S&P 500 index affects consumer credit. The best-fitting model of consumer credit is

$$\underset{}{y_t} = \underset{(6.66)}{0.0031} + \underset{(20.87)}{0.61} y_{t-1} + (\underset{(-3.52)}{-0.0026} + \underset{(1.02)}{0.08} y_{t-1}) \left[1 + \exp\left(-3.23\,(h_t - 2.103)\right)\right]^{-1}, \tag{9}$$

where y_t denotes the growth rate of consumer credit.

Panel A of Figure 6 shows monthly U.S. consumer credit along with the conditional variance of the S&P 500 index estimated by an EGARCH(1,1) model. Recessions, as defined by the NBER, are represented by shaded areas of the figure. On inspection, consumer credit growth seems to decline with the onset of a recession. In Panel B of Figure 6, we show the values of the transition function

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TABLE 3. Long-run equilibrium for positive and negative shocks

	Lags	Equilibrium suggested from the linear model	High uncertainty regime equilibrium	Low uncertainty regime equilibrium	Difference between high and linear equilibrium	Difference between low and linear equilibrium
			Linear models			
Industrial production	2	0.00250				
Durable goods	1	0.00266				
Employment	3	0.00140				
Consumer credit	3	0.00633				
Bank loans	5	0.00620				
Bank cash	1	0.00632				
			LSTAR models			
S&P var—ind. prod.			−0.0054	0.00417	**−0.00790**	0.00167
S&P var—CC			0.0016	0.00795	**−0.00473**	0.00162
S&P var—emp.			0.0000	0.0021	**−0.00140**	0.00070
BOS— ind. prod.			−0.0015	0.0043	**−0.00400**	0.00180
BOS—durables			−0.0187	0.0087	**−0.02136**	0.00604
BOS—CC			0.0054	0.0075	−0.00093	**0.00117**
Index—ind. prod.			0.0000	0.0028	**−0.00250**	0.00003
Index—loans			0.0000	0.0083	**−0.00620**	0.00210
Index—CC			0.0011	0.0072	**−0.00528**	0.00087
Int. spread—cash			0.1137	0.00397	**0.10738**	−0.00235

Note: The numbers of lags for the linear models and the LSTAR models are selected by minimizing the BIC. Each of the equilibria for the LSTAR models is obtained from the coefficient estimates in Table 2. The numbers in bold indicate whether the absolute value of the difference between the high-uncertainty equilibrium and the equilibrium suggested from the linear model or the difference between the low-uncertainty equilibrium and the equilibrium suggested from the linear model is greater.

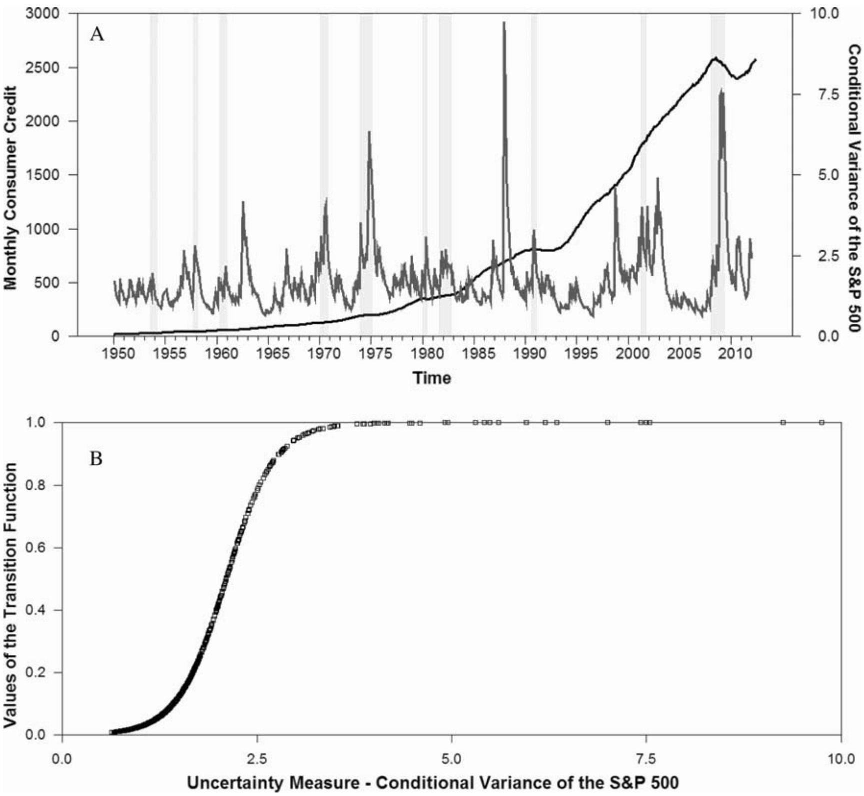

FIGURE 6. Uncertainty and consumer credit. (A) Conditional variance of the S&P 500 and monthly U.S. consumer credit; (B) values of the transition function in the LSTAR model. Panel A shows the conditional variance estimated by an EGARCH(1,1) model normalized by dividing by the standard deviation of the series, along with monthly consumer credit.

against the estimated values of h_t. The centrality parameter $c = 2.103$ is near the center of the estimated h_t series shown in Panel A. When uncertainty is low, the skeleton of (9) indicates that the long-run equilibrium value of consumer credit is $0.00795 = 0.0031/(1 - 0.61)$. However, when uncertainty is high, the long-run equilibrium of consumer credit is only $0.00161 = (0.0031 - 0.0026)/(1 - 0.61 - 0.08)$. Therefore, consumer credit slows considerably during times of high uncertainty.

6.2. Historical Decomposition

We perform two counterfactual analyses to show the effects of uncertainty on consumer credit: one for 2000:M1−2012:M1 and the other for 2010:M6−2012:M6. The historical decomposition for 2000:M1−2012:M1 is shown in Panel A of Figure 7. Similarly to our aforementioned historical decompositions, during this

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first period we set the value of uncertainty equal to its average value for the 1990s (i.e., $h_t = 1.48$ and the transition function is approximately zero in each time period). Then we set the initial condition for y_t equal to the actual value of consumer credit growth for 2000:M1 and iterate forward. Panel A of Figure 7 shows the recursive counterfactual values of consumer credit compared with the actual values. Clearly, if the average level of uncertainty values for the 1990s had continued, we would have expected strong growth in consumer credit. Specifically, the level of consumer credit at the end of the twelve-year period is estimated to be almost 90% higher than the actual value.

Panel B of Figure 7 shows the time series plot of consumer credit for the second historical decomposition, 2010:M6–2012:M6. We set the value of uncertainty equal to its average during the recent financial crisis (i.e., h_t is fixed at 4.98, so that the transition function is approximately one). Then we set the initial condition y_t equal to the actual value for 2010:M6 and iterate forward. As shown in Figure 7, Panel B, if the uncertainty level had remained constant at its average level for the financial crisis, consumer credit would have grown at a lower rate. Note that over the two-year period, counterfactual consumer credit would have been approximately 5% lower than actual consumer credit. The fact that the differential between the actual and counterfactual values is relatively small compared to other sectors reflects the tendency of banks to hoard cash. As shown in the last column of Table 2, high uncertainty increases the intercept of bank cash holdings from 0.004 to 0.044 and the persistence parameter from -0.007 to 0.613. Therefore, even in the absence of additional positive uncertainty shocks, the increase in the persistence parameter means that banks continue to hoard cash and restrict the amount of consumer credit.

6.3. Impulse Responses

Panel C of Figure 7 shows the impulse responses of a continuing positive and a continuing negative uncertainty shock to consumer credit. We initialize the model in period one by setting the magnitude of uncertainty equal to the centrality parameter c and the log difference of consumer credit equal to the equilibrium suggested from the linear model. Thus, the transition function equals $^1/_2$ in period one before the uncertainty shocks and consumer credit is equal to 0.00633. For a continuing positive (negative) uncertainty shock, the value of uncertainty in every period is determined by setting the residuals $\varepsilon^*_{1t+1}, \varepsilon^*_{1t+2}, \ldots, \varepsilon^*_{1t+12}$ equal to a minus (plus)-one-standard-deviation innovation of the residuals in (5). As illustrated by the reflection of the continuing positive uncertainty shock shown in Panel C of Figure 7, increases in uncertainty have larger effects on consumer credit than decreases in uncertainty. Specifically, consumer credit falls from 0.00633 to 0.0016 for the continuing positive uncertainty shock and rises only from 0.0063 to 0.00795 for the continuing negative uncertainty shock.

We investigate how different-sized shocks would affect consumer credit were they all to occur in 2008:12. In Panel A of Figure 8, the solid, dotted, and dashed

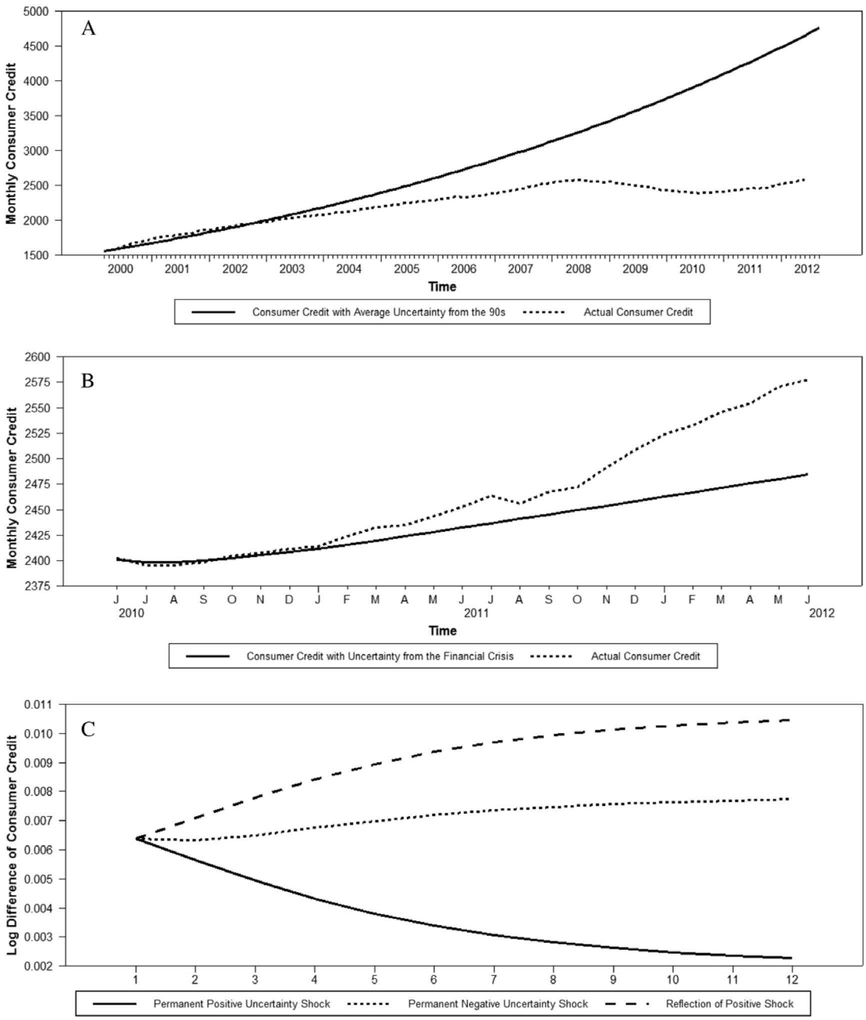

FIGURE 7. Historical decompositions and continuing uncertainty shocks. (A) Decomposition if uncertainty equals its average value during the 1990s; (B) decomposition if uncertainty equals its average value during the financial crisis; (C) effects of continuing shocks to uncertainty. Panel C shows the asymmetric effects of continuing positive and negative uncertainty shocks. The reflection of the positive shock shows that positive shocks have greater effects than negative shocks.

lines show bootstrapped mean values of $+2$, $+1$, and -1 standard deviation temporary shocks to consumer credit, respectively. Notice that in each case the uncertainty shocks slow consumer credit for the first three months after the shock. Moreover, changing the magnitude of the shock has a non-proportional effect on consumer credit. Although the differential between a $+1$ and a -1 standard

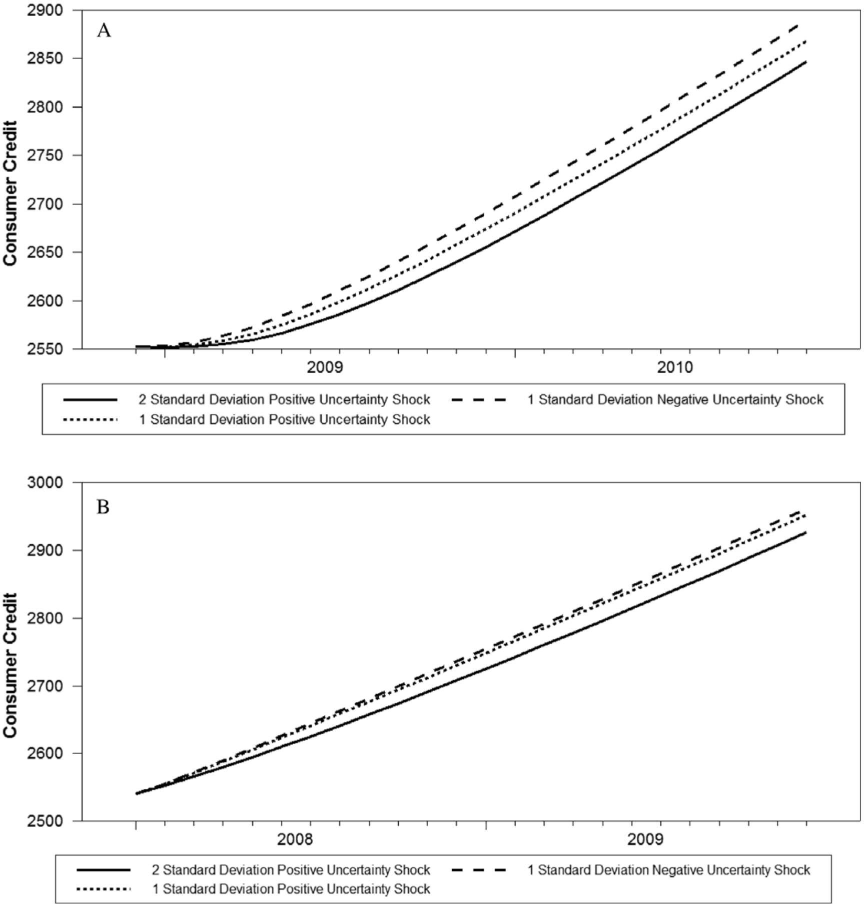

FIGURE 8. The asymmetric effects of temporary uncertainty shocks. (A) Impulse responses to uncertainty shocks during the financial crisis (2008:12); (B) impulse responses to uncertainty shocks before the financial crisis (2008:1). The figure shows the impulse responses to a temporary positive one-standard-deviation uncertainty shock, a temporary positive two-standard-deviation uncertainty shock, and a temporary negative one-standard-deviation uncertainty shock before and during the financial crisis. All lines show mean estimates of each impulse response.

deviation shock is twice that of a $+1$ to $+2$ standard deviation shock, the magnitude of the effects on consumer credit is about the same.

Panel B of Figure 8 repeats the exercise assuming that shocks of the same size occurred in 2008:1. In this case, the temporary uncertainty shocks barely affect consumer credit. Even large positive uncertainty shocks do not affect consumer credit substantially. The key point is that the timing of temporary uncertainty shocks matters more than the magnitude of temporary uncertainty shocks.

7. CONCLUSION

We contribute to the growing literature on uncertainty by investigating the asymmetric effects of uncertainty on macroeconomic activity before and during the recent financial crisis. Instead of estimating a conventional linear model, we estimate uncertainty using an EGARCH model to allow positive and negative shocks to have asymmetric effects, and estimate output using an LSTAR model. We show that increases in uncertainty have greater effects than decreases in uncertainty on a number of important macroeconomic variables. These results are robust to several measures of uncertainty and important macroeconomic variables. We also provide two potential answers to the question of the direction of causality. First, in Section 5.2, we develop a nonlinear VAR model and show that the coefficient on output is insignificant in the equation for uncertainty. Second, uncertainty is shown to affect many different sectors of the economy, which is unlikely to be the case if output is truly causing the changes in uncertainty.

Because linear models are essentially averages across the two types of shocks, they underestimate the economic effects of increases in the level of uncertainty. Moreover, the timing of the shocks is also crucial, because uncertainty shocks that occur during severe recessions are likely to have much more profound effects than shocks of similar size occurring during expansions. Our findings suggest that policy makers should be especially concerned about minimizing the level of uncertainty during downturns such as the recent financial crisis.

Although we find unidirectional causality between uncertainty and the key macroeconomic variables, there may be unobservable business cycle phenomena that simultaneously affect both uncertainty and the macroeconomic variables. Nevertheless, the asymmetric pattern we find is consistent across industrial production, durable goods production, employment, consumer credit, bank loans, and bank cash.

NOTES

1. There is another strand of literature that looks at the idea of the irreversibility of investment. See, for example, Arrow (1968), Abel and Eberly (1994), and Bertola and Caballero (1994).

2. Grier et al. (2004) find asymmetric effects from growth volatility and inflation volatility on output growth and inflation using a GARCH-M model. Their results show that growth volatility leads to significantly lower average growth.

3. Bloom (2009) shows that stock market volatility is strongly correlated with other measures of uncertainty and is therefore a good proxy for macroeconomic uncertainty.

4. As a robustness check, Bloom (2009) also uses the entire HP detrended volatility series, and the results are virtually unchanged, with output declining quickly and then overshooting.

5. An alternative measure of stock market volatility used in Section 5.2 is the Chicago Board of Options Exchange VXO index. The main drawback to using this series is the smaller sample size. The VXO is only available beginning in 1986. The correlation between our conditional variance of the S&P 500 and the VXO index is 0.71. Our results in Section 3 hold if the VXO index is used instead of the conditional variance of the S&P 500.

6. Using the HP filter can be problematic. Cogley and Nason (1995) show that the HP filter can generate business cycle dynamics even if none are present in the data. When the data are difference

stationary, as in the volatility series of the S&P 500, the HP filter can amplify growth cycles at business cycle frequencies. Harvey and Jaeger (1993) also show that applying the HP filter can lead to spurious cyclical behavior.

7. Nevertheless, using the HP filter on our data yields results that are not different from those reported.

8. Further details can be found in van Dijk et al. (2002)

9. See Section 6 for a complete analysis of additional variables and the Data Appendix for the definitions of the variables.

10. We calculate the AIC and BIC as $T\ln(\text{ssr}) + 2r$ and $T\ln(\text{ssr}) + r\ln(T)$, respectively, where r is the number of estimated parameters and ssr is the sum of squared residuals.

11. To ensure parsimonious nonlinear models, we select the lag lengths for this model and the models in Section 6 using the BIC. In each case, the BIC selects an LSTAR model with one lag.

12. A t-test for γ is not reported, because the parameters in the LSTAR model are undefined when $\gamma = 0$. Likewise, the variance is always positive. Therefore, a t-test for $c = 0$ is also not reported.

13. Note that for our counterfactual analyses and generalized impulse responses, we sum the changes in output growth to obtain the estimated levels of industrial production.

14. Table 3 reports these same results in a different manner: 0.0025 is the equilibrium suggested from the linear model of industrial production, -0.0054 is the high-uncertainty regime equilibrium, and 0.00417 is the low-uncertainty regime equilibrium.

15. Using the VXO index instead of the conditional variance of the S&P 500 allows us to estimate a simple VAR model instead of a complicated multivariate GARCH-M model. The results from the VAR are also easier to interpret.

16. This can be seen graphically in Figure 2, Panel C, and Figure 7, Panel C.

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DATA APPENDIX

In this Appendix, we describe the data for our measures of uncertainty and macroeconomic variables (see Table A.1). Most of the measures come from the Federal Reserve Economic Database (FRED). More information on specific variables follows.

A.1. EMPLOYMENT

Employment is the log difference in monthly total nonfarm employees from 1950:1 to 2012:8.

A.2. CONSUMER CREDIT

Consumer credit is the log difference in total monthly consumer credit owned and securitized, outstanding from 1950:1 to 2012:6.

A.3. BANK LOANS

Bank loans is the log difference in commercial and industrial loans at all commercial banks from 1950:1 to 2012:7.

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TABLE A.1. Sources of data

Variable	Data source	Transformation	Time period	Frequency
Industrial production	FRED	Log difference	1950:1–2012:1	Monthly
Durable goods	FRED	Log difference	1950:1–2012:1	Monthly
Employment	FRED	Log difference	1950:1–2012:8	Monthly
Consumer credit	FRED	Log difference	1950:1–2012:6	Monthly
Bank loans	FRED	Log difference	1950:1–2012:7	Monthly
Bank cash	FRED	Log difference	1973:1–2012:7	Monthly
S&P 500 conditional variance	Yahoo Finance	Log difference	1950:1–2012:1	Monthly
Interest rate spread	FRED	Level	1953:4–2012:1	Monthly
Business outlook survey	Philadelphia Fed	Level	1968:5–2012:1	Monthly
Uncertainty index	Baker et al. (2012)	Level	1985:1–2012:1	Monthly
VXO index	CBOE	Level	1986:7–2012:8	Monthly

A.4. BANK CASH

Bank cash is the log difference in cash assets at all commercial banks from 1973:1 to 2012:7.

A.5. S&P 500 CONDITIONAL VARIANCE

The S&P 500 index is the monthly opening price on the first trading day of the month. For example, the value of the S&P index for the first month of 1950 is the opening value of the index on January 3, 1950. We use an EGARCH(1,1) model as our estimate of the conditional variance of the S&P 500, as shown in Section 2.5.

A.6. INTEREST RATE SPREAD

For our second measure of uncertainty we follow Gilchrist et al. (2014) and use the spread between the 30-year Baa corporate bond and the 30-year Treasury bond. If the 30-year bond is not available, we use the 20-year bond.

A.7. BUSINESS OUTLOOK SURVEY

Our next measure comes from Bachmann et al. (2013). It quantifies disagreements in the Philadelphia FED District Business Outlook Survey (BOS). In particular, we use the response of manufacturing firms to the following question from the survey: "What is your evaluation of the level of general business activity six months from now vs. current month: decrease, no change, increase?" We subsequently calculate uncertainty as

$$\begin{aligned}\text{uncertainty}_t = {} & \text{sqrt}(\text{Frac}_t\,(\text{increase}) + \text{Frac}_t\,(\text{decrease}) \\ & - (\text{Frac}_t\,(\text{increase}) - \text{Frac}_t\,(\text{decrease}))_{)}^{2},\end{aligned}$$

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where Fract_t(increase) is the fraction of individuals that believe that business conditions six months from time t will increase, and Fract_t(decrease) is defined similarly.

A.8. UNCERTAINTY INDEX

The uncertainty index is the monthly policy-related uncertainty index of Baker et al. (2012), which spans January 1985 to January 2012 and combines three index components. The first quantifies the number of references to policy-related uncertainty in ten leading newspapers. The component is the number of federal tax code provisions set to expire in future years, and the final component is the extent of disagreement between economic forecasters over future federal government purchases and consumer price index (CPI) levels.

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