EMPIRICAL ESSAYS ON UNCERTAINTY

AND ECONOMIC BEHAVIOR

by

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ABSTRACT

My dissertation looks at the new and growing field of macroeconomic uncertainty. It consists of three empirical essays on different measures of macroeconomic uncertainty and how uncertainty affects macroeconomic behavior.

The first essay uses a new uncertainty index from Baker et al. (2012). We evaluate the time-varying correlation between macroeconomic uncertainty, inflation, and output. Estimation results from a multivariate DCC-GARCH model reveal that the sign of the correlation between macroeconomic uncertainty and inflation changed from negative to positive during the late 1990s, whereas the correlation between uncertainty and output is consistently negative.

In the second essay, we propose domestic uncertainty shocks may serve as a channel through which business cycles are transmitted internationally. To quantify uncertainty, we use two measures from the current literature and estimate structural vector autoregressions to evaluate the effects U.S. uncertainty shocks have on the Japanese and British economies. Our results suggest U.S. uncertainty shocks have international effects consistent with a demand shock in the context of an open-economy IS/LM model with sticky prices.

For the final essay we estimate a number of macroeconomic variables as logistic smooth transition autoregressive (LSTAR) processes with uncertainty as the transition variable. Nonlinear estimation allows us to answer several interesting questions left unanswered by a linear model. For a number of important macroeconomic variables, we show (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 concerning the consequences of uncertainty are underestimated in circumstances such as the recent financial crisis.

DEDICATION

To my parents, Jimmy and Kay Jones.

LIST OF ABBREVIATIONS AND SYMBOLS

DCC	Dynamic Conditional Correlation
GARCH	Generalized Autoregressive Conditional Heteroskedastic
IS/LM	Investment Saving/Liquidity Preference Money Supply
LSTAR	Logistic Smooth Transition Autoregressive
CPI	Consumer Price Index
GDP	Gross Domestic Product
VAR	Vector Autoregression
ARCH	Autoregressive Conditional Heteroskedastic
LM	Lagrange Multiplier
NBER	National Bureau of Economic Research
U.S.	United States
U.K.	United Kingdom
SVAR	Structural Vector Autoregression
IFS	International Financial Statistics
AIC	Akaike Information Criterion
SBC	Schwartz Bayesian Criterion
S&P 500	Standard and Poor's 500 Index
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedastic

HP	Hodrick-Prescott
STAR	Smooth Transition Autoregressive
BIC	Bayesian Information Criterion
VXO	Volatility Index

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CHAPTER 1

INTRODUCTION

This introduction will address the following questions in order to provide a context for my dissertation:

- What is macroeconomic uncertainty?
- What are the potential channels through which uncertainty affects macroeconomic behavior?

Uncertainty is inherently difficult to define because it varies across consumers, firms, and policymakers over future outcomes. Knight (1921) defined uncertainty as risk that is impossible to calculate or forecast. Moreover, Knight (1921) defined risk as known probabilities over known events. A pure measure of uncertainty in terms of Knight's (1921) definition is impossible to proxy since it is, by definition, immeasurable. Therefore, any measure of uncertainty, must in some sense, be a combination of both risk and uncertainty.

Measures of uncertainty can be divided into macro and micro measures. Some of the proxies used in the literature to approximate macro uncertainty are stock market volatility, news mentions of uncertainty, and forecaster disagreement. On the other hand, measures of micro uncertainty are based on industry, firm, plant, or individual product data. Examples include

industry-level output growth, firm stock-return variation, plant-level growth rates, and individual product prices. Macro and micro measures of uncertainty appear to be countercyclical.[1]

My dissertation, which focuses on the effects of macroeconomic uncertainty, uses four measures of uncertainty. Specifically, I use the following: stock market volatility (Bloom (2009)), an interest rate spread (Gilchrist, Sim, and Zakrajsek(2010)), business outlook survey data (Bachmann, Elstner, and Sims (2013)), and a policy-related uncertainty index (Baker et al. (2012)).

I use a generalized autoregressive conditional heteroskedastic (GARCH) model as my estimate of stock market volatility. An interest rate spread, which serves as my second proxy for uncertainty, measures the difference between the 30-year Baa corporate bond and the 30-year Treasury bond. Bachmann, Elstner, and Sims (2013) quantify disagreements in The Philadelphia FED District Business Outlook Survey, and I use this as my third measure of uncertainty. In particular, I 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. the current month: decrease, no change, increase?" Uncertainty is calculated using the following formula:

$$uncertainty_t = sqrt(Frac_t(increase) + Frac_t(decrease) - (Frac_t(increase) - Frac_t(decrease))^2)$$

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.

My final measure of uncertainty is the monthly, policy-related uncertainty index by Baker et al. (2012) which combines three index components. The first component quantifies the

[1] Bloom (2013) discusses several papers that document how different macro and micro uncertainty measures are countercyclical.

number of references to policy-related uncertainty in ten leading newspapers. The second is the number of federal tax code provisions set to expire in future years, and the final is the extent of disagreement between economic forecasters over future, federal government purchases and consumer price index (CPI) levels. These three components are combined to obtain a measure of policy-related uncertainty.

While my dissertation focuses on the empirical effects of macroeconomic uncertainty, I want to briefly discuss the theoretical literature and the potential channels through which uncertainty affects macroeconomic activity. The literature emphasizes three channels through which macroeconomic uncertainty can negatively affect macroeconomic behavior: a real option channel, a risk premium channel, and a precautionary savings channel.

Bernanke (1983) began a body of literature looking at the idea that firms have a series of call options on potential new investments.[2] For example, a business that owns land has the call option to build a new store on the land, or if the future is uncertain, the business can delay the decision until a later time. A high level of uncertainty causes the option value of delay to be higher. The result is that businesses are cautious about actions such as investment and hiring during times of high uncertainty.

Another channel through which uncertainty can potentially affect growth is an increasing risk premium. Investors want to be compensated for higher risk and during times of high uncertainty investors are likely to raise the cost of financing. Uncertainty increases the cost of financing and raises the probability of default by expanding the default outcomes. As a result, as the risk of default increases banks charge higher interest rates, and this reduces macroeconomic growth. Several papers look at the impact of uncertainty in the presence of financial constraints

[2] Other papers include Brennan and Schwartz (1985), McDonald and Siegel (1986), and Dixit and Pindyck (1994).

including Arellano, Bai, and Kehoe (2010), Christiano, Motto, and Rostagno (2014), and Gilchrist, Sim, and Zakrasjek (2010).

The final channel explored in the theoretical literature is precautionary savings. The idea is that an increase in uncertainty increases precautionary savings which reduces consumption expenditure and therefore decreases economic growth. This can have a crippling effect in small, open economies as argued in Fernandez-Villaverde et al. (2011). In these types of economies, high uncertainty can cause domestic savers to move money abroad which reduces local investment. However, the effect is less clear in large economies such as the United States.

In conclusion, it appears uncertainty is countercyclical and has a negative impact on growth, investment, hiring, and consumption. Uncertainty appears to rise in recessions because shocks that tend to cause recessions also tend to increase uncertainty. Moreover, uncertainty acts to amplify these shocks and often contributes to economic slowdowns. Bloom (2013) estimates that the uncertainty shock which occurred during the Great Recession accounted for approximately one third of the 9% drop in GDP during 2008-2009. Thus, there is room for further research on the causes and effects of uncertainty.

CHAPTER 2

THE TIME-VARYING CORRELATION BETWEEN UNCERTAINTY, OUTPUT, AND INFLATION: EVIDENCE FROM A DCC-GARCH MODEL

2.1 Introduction

Since the financial crisis of 2008, a literature examining the macroeconomic effects of uncertainty has developed. Bloom (2009), Bloom et al. (2009), Gilchrist et al. (2010), and Panousi and Papanikolaou (2011) develop models in which uncertainty shocks adversely affect output. On the other hand, Bachmann et al. (2010) find little empirical evidence supporting such a causal relationship and conclude that recessions breed uncertainty. One disagreement in the current literature regards the measure of uncertainty. Recently, Baker et al. (2012) addressed this by developing a policy-related uncertainty index. Our aim is to explore the historical uncertainty-output and uncertainty-inflation relationships using Engle's (2002) dynamic conditional correlation (DCC) GARCH model. The time-varying nature of our approach allows us to capture the uncertainty-output and uncertainty-inflation relationships in different states of the business cycle since the late 1980s. Our results follow: (1) the correlation between inflation and uncertainty turns from negative to positive during the late 1990s and early 2000s, and (2) the correlation between uncertainty and output is consistently negative.

2.2 Methodology

As Figure 1 shows, all three time series exhibit conditional heteroskedasticity characteristics. Therefore, we choose to follow Hamilton (2008) and model the series as GARCH

processes. In particular, we adopt Engle's (2002) multivariate GARCH model allowing for time-varying correlations.

Let $y_t = [y_{1t}, y_{2t}]'$ be a 2x1 vector containing the data series. We represent the conditional mean equations by the following reduced-form VAR:

$$A(L)y_t = \varepsilon_t \qquad \varepsilon_t \sim N(0, H_t) \qquad t = 1, \ldots\ldots T \tag{1}$$

where *A(L)* is a matrix in the lag operator *L*, and $\varepsilon_t = [\varepsilon_{1t}, \varepsilon_{2t}]'$ is a vector of innovations. The ε_t vector has the following conditional variance-covariance matrix:

$$H_t = D_t R_t D_t$$

where $D_t = diag\{\sqrt{h_{it}}\}$ is a 2x2 matrix containing the time-varying standard deviations from univariate GARCH models and $R_t = \{\rho_{ij}\}_t$ for $i, j = 1, 2$ is a correlation matrix containing conditional correlation coefficients. The standard deviations in D_t are governed by the following univariate GARCH*(P,Q)* process:

$$h_{it} = \gamma_i + \sum_{p=1}^{P_i} \alpha_{ip} \varepsilon_{it-p}^2 + \sum_{q=1}^{Q_i} \beta_{iq} h_{iq-q} \qquad \forall\, i = 1,2. \tag{2}$$

Engle's (2002) framework consists of the following *DCC(M,N)* structure:

$$R_t = Q_t^{*-1}\, Q_t\, Q_t^{*-1},$$

where

$$Q_t = \left(1 - \sum_{m=1}^{M} a_m - \sum_{n=1}^{N} b_n\right)\overline{Q} + \sum_{m=1}^{M} a_m\,(\varepsilon_{t-m}\varepsilon_{t-m}) + \sum_{n=1}^{N} b_n\, Q_{t-n}. \tag{3}$$

$\overline{Q}$ is the time-invariant variance-covariance obtained from estimating (2), and

Q_t^* is a 2x2 diagonal matrix containing the square root of the diagonal elements of Q_t. Our primary focus is on the conditional correlation $\rho_{12,t} = q_{12,t}/\sqrt{q_{11,t}q_{22,t}}$ in R_t.

2.3 Data

We use the monthly, policy-related uncertainty index by Baker et al. (2012) which spans from January 1985 through January 2012 and combines three index components. The first quantifies the number of references to policy-related uncertainty in ten, leading newspapers. The next component is the number of federal tax code provisions set to expire in future years, and the final is the extent of disagreement among economic forecasters over future federal government purchases and consumer price index (CPI) levels. Output is defined as 1200 times the log monthly change in industrial production, and inflation is defined similarly using the CPI. Before estimating the DCC model, we implement unit root and ARCH tests to ensure stationarity and test for heteroskadasticity. Table 1 contains the results.

Using augmented Dickey-Fuller tests, output and inflation are found to be stationary while the uncertainty index contains a unit root. However, since it seems unlikely that macroeconomic uncertainty follows a random walk and Perron's (1989) analyses showing that structural breaks can lead to erroneously accepting unit roots, we also implement the Zivot and Andrews (1992) unit root test. Table 1 shows that the Zivot and Andrews test indicates that uncertainty is stationary in levels with a structural break occurring in August 2007. To account for the structural break, we estimate the conditional mean of uncertainty in Equation 1 with a dummy variable (i.e. $D_L=1$) for all $t \geq$ August 2007 (i.e. $D_L= 0$ otherwise). The ARCH LM test rejects the null hypothesis of homoskedasticity for all three variables indicating that ARCH-type models are appropriate.

2.4 Results

To investigate the results of Bachmann et al. (2010), we include the conditional variances $h_{i,t}$ of each variable in the mean equations in (1). If their hypothesis that recessions breed

uncertainty is correct, then the coefficients on the conditional variances of output and inflation should be positive and statistically significant in the conditional mean equation of uncertainty.

Table 2 reports the results from the estimated models. Panel A contains the results from the mean equations, Panel B contains the conditional variance estimates, and Panel C contains the diagnostic tests. Because of the limited number of uncertainty observations, we select the lag lengths in the mean equations using the minimum number of lags it takes to rid the standardized and squared standardized residuals of serial correlation. The Ljung-Box Q-statistics in Panel C suggest both of the models are adequately estimated. The uncertainty conditional variance coefficient has a statistically significant negative effect on the inflation rate (displayed in Model 1 of Table 2) but no significant impact on output. Interestingly, the output conditional variance coefficient has a statistically positive effect on the level of uncertainty consistent with Bachmann et al. (2010) results.

Figures 2 and 3 display the time-varying correlations from the two models along with 90% confidence intervals. Shaded portions of the figures are NBER recession dates and the lines are dates during which the U.S. experienced oil price shocks as determined by Hamilton (2009). The most striking feature of the figures is the change in the correlation between uncertainty and inflation in Figure 2. It ranges from -0.14 in the 1980s to +0.20 in 2006. As expected, during the simultaneous recession and oil price shock of 1991-1992 the correlation between inflation and uncertainty increases. During the subsequent two recessions in 2001 and 2007-2009 the correlation falls, but increases again during the oil shocks of 2005-2008.

In Figure 3, the correlation between uncertainty and output is consistently negative regardless of the state of the business cycle. There is no material change in the correlation during the oil price shock of 1991, but it does become more negative during the 2005-2008 oil price

shock. Note that the correlation has become less negative since the onset of the European debt crisis in 2010.

2.5 Conclusion

Using a new uncertainty index from Baker et al. (2012), we evaluate the correlation between macroeconomic uncertainty, inflation, and output. Empirical results based on a DCC-GARCH model confirm that the correlation between uncertainty and output is consistently negative since the 1980s. Somewhat unexpectedly, our results also indicate that the correlation between uncertainty and inflation became positive during the late 1990s and early 2000s. One hypothesis for this change in the correlation is the increase in crude oil prices which begins during the early 2000s and continues until the financial crisis in 2008. During the crisis, crude oil prices drop precipitously and the correlation briefly turns negative. Pinpointing the factors that cause the change in the correlation between inflation and uncertainty would be an interesting line of future research.

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Table 2.1. Unit Root and Heteroskedasticity Tests

Unit Root Tests[1]:	**Variable:**		
	Uncertainty	*Inflation*	*Output*
Augmented D-F	-1.39	-5.06***	-4.35***
Zivot-Andrews[2]	-5.31**		
Heteroskedasticity Test:			
ARCH (12) LM Test	243.794***	38.184***	38.25***

** Denotes statistical significance at the 95% level.
*** Denotes statistical significance at the 99% level.
[1]Under the null hypothesis, the series is a unit root process.
[2]The estimated break date is August 2007.

Table 2.2. Bivariate DCC – GARCH Model

Panel A Mean Estimates (std. errors in parentheses)

Model 1: Uncertainty/Inflation				**Model 2: Uncertainty/Output**		
	u_t	π_t			u_t	y_t
Constant	9.620	1.725		*Constant*	13.779	-2.100
	(3.744)	(0.559)			(3.851)	(1.415)
π_{t-1}	0.094	0.345		y_{t-1}	-0.098	-0.004
	(0.241)	(0.061)			(0.108)	(0.066)
π_{t-2}	0.116	-0.075		y_{t-2}	-0.077	0.262
	(0.241)	(0.061)			(0.105)	(0.052)
π_{t-3}	0.459	0.058		y_{t-3}	-0.098	0.188
	(0.235)	(0.059)			(0.101)	(0.045)
π_{t-4}	0.146	0.039		y_{t-4}	-0.142	0.099
	(0.251)	(0.057)			(0.100)	(0.047)
π_{t-5}	-0.088	0.068		y_{t-5}	-0.085	0.064
	(0.257)	(0.055)			(0.095)	(0.050)
π_{t-6}	-0.101	-0.042		y_{t-6}	-0.006	0.084
	(0.246)	(0.058)			(0.100)	(0.046)
π_{t-7}	0.862	0.072		y_{t-7}	-0.093	-0.021
	(0.225)	(0.052)			(0.096)	(0.046)
π_{t-8}	-0.277	-0.071		y_{t-8}	-0.023	0.047
	(0.235)	(0.052)			(0.092)	(1.030)
π_{t-9}	-0.144	0.054		y_{t-9}	0.171	0.054
	(0.212)	(0.046)			(0.101)	(1.253)
u_{t-1}	0.694	-0.003		u_{t-1}	0.671	-0.066
	(0.053)	(0.007)			(0.064)	(0.021)
u_{t-2}	0.068	-0.006		u_{t-2}	0.181	-0.018
	(0.061)	(0.007)			(0.069)	(0.021)
u_{t-3}	-0.239	0.020		u_{t-3}	-0.304	-0.013
	(0.072)	(0.008)			(0.070)	(0.020)
u_{t-4}	0.230	-0.016		u_{t-4}	0.193	0.081
	(0.041)	(0.008)			(0.048)	(0.021)
u_{t-5}	0.035	0.010		u_{t-5}	0.053	-0.040
	(0.032)	(0.007)			(0.060)	(0.023)
u_{t-6}	-0.170	0.013		u_{t-6}	-0.093	0.054
	(0.052)	(0.009)			(0.069)	(0.022)
u_{t-7}	0.069	0.001		u_{t-7}	-0.002	-0.012
	(0.061)	(0.009)			(0.064)	(0.019)
u_{t-8}	0.034	-0.018		u_{t-8}	0.104	-0.002
	(0.063)	(0.008)			(0.069)	(0.022)
u_{t-9}	0.111	0.003		u_{t-9}	0.034	0.033
	(0.051)	(0.007)			(0.052)	(0.021)
hu_t	0.007	-0.001		hu_t	0.001	0.001
	(0.005)	(0.000)			(0.006)	(0.001)
$h\pi_t$	0.133	-0.037		hy_t	0.057	0.015
	(0.086)	(0.026)			(0.016)	(0.009)
D_L	12.755			D_L	11.174	
	(2.776)				(2.537)	

Panel B Conditional Variance Estimates (std. errors in parentheses)

	Model 1: Uncertainty/Inflation			***Model 2: Uncertainty/Output***	
	h_{u_t}	h_{π_t}		h_{u_t}	h_{y_t}
γ_1	49.67 (17.02)	0.395 (0.163)		17.85 (3.12)	24.90 (1.66)
α_1	0.615 (0.129)	0.285 (0.0515)		0.446 (0.03)	0.473 (0.048)
β_1	0.284 (0.106)	0.692 (0.049)		0.564 (0.017)	0.023 (0.042)
a	0.017 (0.010)			0.0405 (0.015)	
b	0.982 (0.011)			0.935 (0.032)	

Panel C Ljung-Box Q-statistics (significance values in parentheses)

	Model 1: Uncertainty/Inflation			**Model 2: Uncertainty/Output**	
Standardized Residuals (*Lags*)	**Uncertainty**	**Inflation**		**Uncertainty**	**Output**
4	2.617 (0.62)	1.716 (0.78)		2.328 (0.67)	0.965 (0.91)
8	8.17 (0.41)	7.181 (0.517)		4.580 (0.80)	4.379 (0.82)
12	16.87 (0.15)	19.66 (0.07)		9.883 (0.62)	6.658 (0.87)
Squared Residuals					
4	0.597 (0.96)	2.69 (0.60)		0.478 (0.97)	2.718 (0.60)
8	2.31 (0.96)	4.72 (0.78)		2.260 (0.97)	5.133 (0.74)
12	16.34 (0.17)	13.37 (0.34)		8.175 (0.77)	8.261 (0.76)

Figure 2.1. Time Series Plots of Uncertainty Index, Inflation, and Output

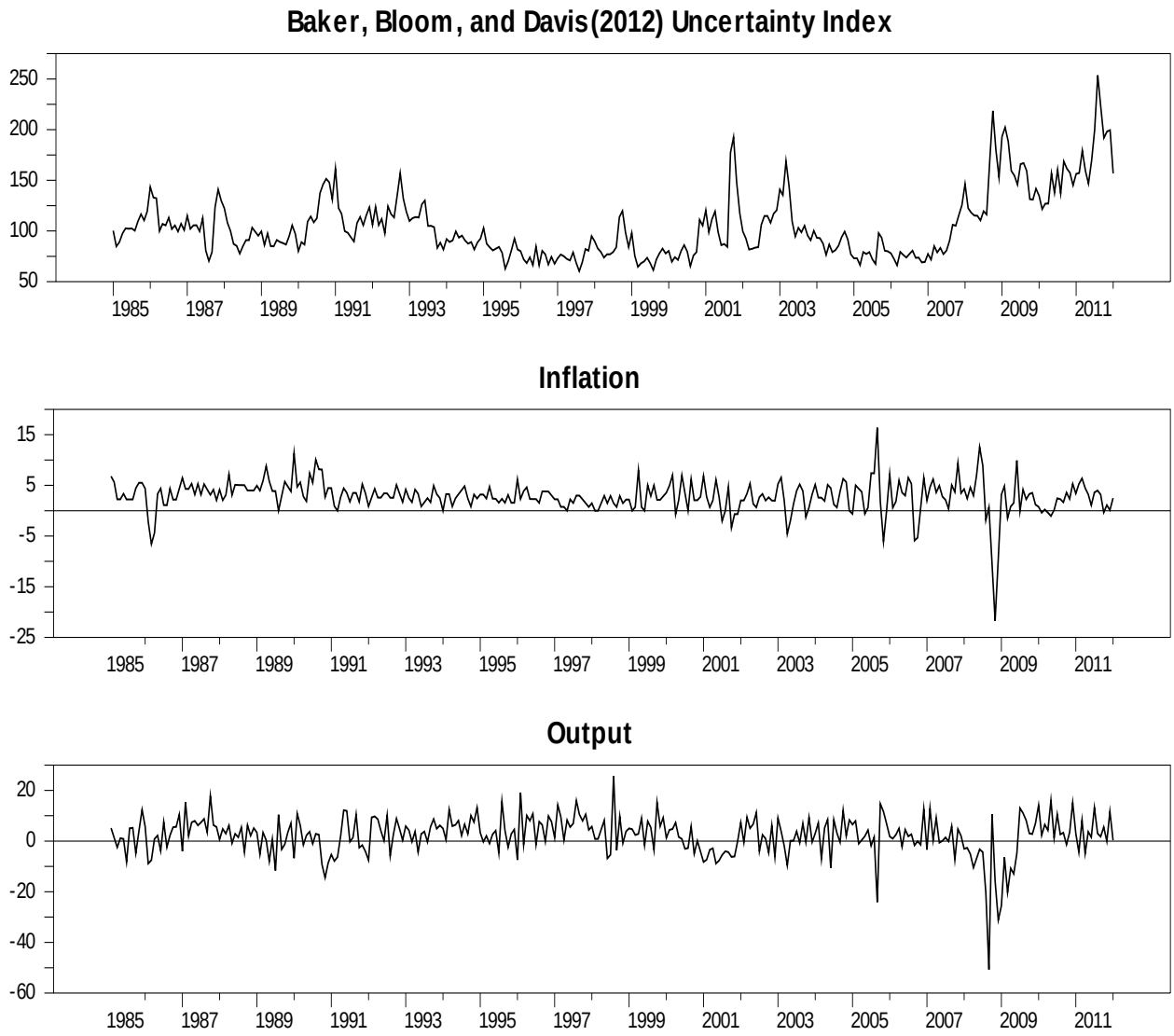


Figure 2.2. Correlations between Uncertainty and Inflation

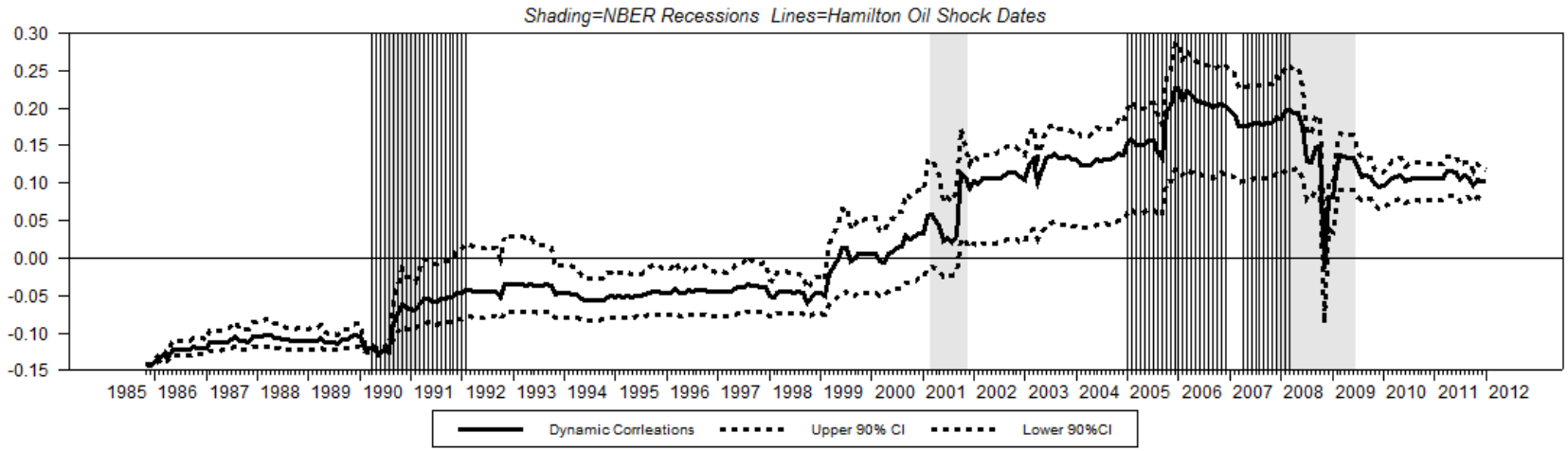
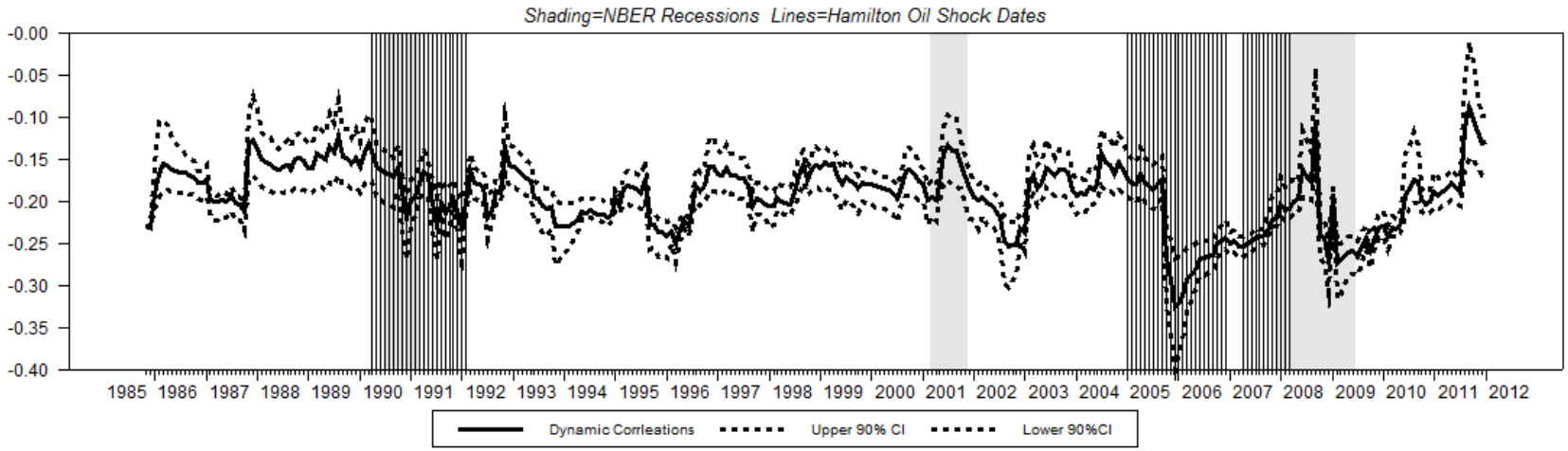


Figure 2.3. Correlations between Uncertainty and Output



CHAPTER 3

THE INTERNATIONAL EFFECTS OF U.S. UNCERTAINTY

3.1 Introduction

In Chairman Bernanke's July 21, 2010 Semiannual Monetary Policy Report to Congress, he surprised many market participants by coining the phrase "unusually uncertain" to describe the U.S. economic outlook. Fittingly, Bernanke (1983) was one of the first to emphasize the impact uncertainty shocks have on macroeconomic activity. While policy makers understand the adverse effects uncertainty may have on the domestic economy by fostering "wait-and-see" attitudes among economic actors,[3] the current academic literature regarding uncertainty shocks is relatively sparse. Bloom (2009) and Bloom et al. (2009) develop structural models in which positive uncertainty shocks lead to temporary reductions in investment and employment causing output to decline. Similarly, Gilchrist, Sim, and Zakrajsek (2009) suggest uncertainty shocks raise the cost of capital leading firms to reduce investment. A related topic that has not received attention in the current literature is the degree to which domestic uncertainty shocks may transmit business cycles internationally. While many business cycle transmission mechanisms have been documented, to our knowledge, uncertainty shocks have not been evaluated in this context.[4]

[3] Consider the FOMC statement after 9/11, "the events of September 11 produced a marked increase in uncertainty […] depressing investment by fostering an increasingly widespread wait-and-see attitude."

[4] Kindleberger (1962) and Meltzer (1976) first noted the significance of trade in the propagation of international business cycles. Frankel and Rose (1998), Clark and van Wincoop (2001), and Baxter and Kouparitsas (2005) all document the positive relationship between trade volume and business cycle synchronization. There are also a variety of trade transmission mechanisms that have been examined that produce business cycle comovements among trading partners: production sharing, dependence on foreign inputs, and common external shocks such as oil price shocks (Burstein et al. 2008; Backus et al., 1995; Baxter, 1995; Stockman and Tesar, 1995; Backus and Crucini, 2000).

We seek to build on Bloom (2009), Bloom et al. (2009), and Gilchrist, Sim and Zakrajsek (2009) and evaluate how U.S. uncertainty shocks affect the economies of large U.S. trading partners. To that end, we estimate SVARs using two measures of uncertainty taken from the above mentioned literature. To preview our results, we find that the international effects of U.S. uncertainty shocks are consistent with a demand shock in an open-economy IS/LM model with sticky prices; U.S. uncertainty shocks induce a statistically significant decline in foreign exports and inflation and cause foreign currencies to appreciate relative to the dollar. The rest of the paper proceeds as follows: Section 2 discusses our uncertainty measures and methodology, Section 3 presents our results of U.S. uncertainty shocks on U.S., Japanese, and British output, Section 4 evaluates the effects of uncertainty shocks on Japanese and British exchange-rates, exports, and inflation rates, Section 5 presents our historical decompositions, and Section 6 concludes.

3.2 Data and Methodology

Three factors influenced our decision to select Japan and the U.K. as the foreign economies of interest. First, both countries have reliable long term data. Second, according to the Census Bureau, as of December 2011, Japan was the fourth largest trading partner with the U.S., and the U.K. was the sixth. Third, exports compose a substantial portion of each country's domestic economy. In 2011, the Japanese economy totaled $5.86 trillion with exports totaling $800.8 billion. In the U.K., 2011 GDP totaled $2.48 trillion with exports amounting to $495.4 billion.

Output for the U.S., Japan, and the U.K. is defined as the log monthly change in industrial production which we obtained from the IFS International Statistics Database for the 1968 – 2010 time period. Since no consensus exists in the literature as to a variable which best

captures macroeconomic uncertainty, our approach is to use two different measures from previous studies. First, as in Gilchrist, Sim, and Zakrajsek (2009), we use the spread between the 30-year Baa corporate bond and the 30-year Treasury bond. Second, similar to Bloom (2009), we use the volatility of the S&P 500.[5] Our data series are shown in Figure 1.

The uncertainty variables likely capture different information in the U.S. economy. Therefore, we estimate the following four-variable SVAR for each measure of U.S. uncertainty:

$$\begin{bmatrix} U_{us_t} \\ y_{us_t} \\ y_{jp_t} \\ y_{uk_t} \end{bmatrix} = \begin{bmatrix} A_{11}(L) & A_{12}(L) & A_{13}(L) & A_{14}(L) \\ A_{21}(L) & A_{22}(L) & A_{23}(L) & A_{24}(L) \\ A_{31}(L) & A_{32}(L) & A_{33}(L) & A_{34}(L) \\ A_{41}(L) & A_{42}(L) & A_{34}(L) & A_{44}(L) \end{bmatrix} \begin{bmatrix} U_{us_{t-1}} \\ y_{us_{t-1}} \\ y_{jp_{t-1}} \\ y_{uk_{t-1}} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \\ e_{4t} \end{bmatrix} \tag{1}$$

where U_{us_t} is U.S. uncertainty, y_{us_t}, y_{jp_t}, and y_{uk_t} are U.S., Japanese, and U.K. output, respectively, A_{ij} (L) are polynomials in the lag operator L, and the e_{it} are regression residuals.

The regression residuals e_{it} are composed of four shocks such that

$$\begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \\ e_{4t} \end{bmatrix} = \begin{bmatrix} g_{11} & g_{12} & g_{13} & g_{14} \\ g_{21} & g_{22} & g_{23} & g_{24} \\ g_{31} & g_{32} & g_{33} & g_{34} \\ g_{41} & g_{42} & g_{34} & g_{44} \end{bmatrix} \begin{bmatrix} \varepsilon_{ut} \\ \varepsilon_{ust} \\ \varepsilon_{jpt} \\ \varepsilon_{ukt} \end{bmatrix} \tag{2}$$

where ε_{ut}, ε_{ust}, ε_{jpt}, and ε_{ukt} are uncertainty, U.S. output shocks, Japanese output shocks, and U.K. output shocks, respectively. Each shock is an i.i.d., zero-mean random variable and all are mutually uncorrelated such that $E_{t-1}\varepsilon_{it}\,\varepsilon_{kt} = 0$ for $i \neq k$. The estimated VAR yields ten distinct elements of the variance-covariance matrix Ee_te_t and the g matrix contains sixteen elements. Therefore it is necessary to impose six additional restrictions to obtain an identified system. For robustness, we implement three different identification schemes. First, we impose a Choleski decomposition such that $g_{12}=g_{13}=g_{14}=g_{23}=g_{24}=g_{34}=0$, therefore matrix (2) becomes

[5] Ideally, we would use the VIX as our measure of S&P 500 volatility as in Bloom (2009). However, VIX data is only available after1986; so, we obtain our S&P 500 volatility by estimating a GARCH (1,1) model. The correlation between the Bloom (2009) series and our estimated conditional volatility is 0.83.

$$\begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \\ e_{4t} \end{bmatrix} = \begin{bmatrix} g_{11} & 0 & 0 & 0 \\ g_{21} & g_{22} & 0 & 0 \\ g_{31} & g_{32} & g_{33} & 0 \\ g_{41} & g_{42} & g_{34} & g_{44} \end{bmatrix} \begin{bmatrix} \varepsilon_{ut} \\ \varepsilon_{ust} \\ \varepsilon_{jpt} \\ \varepsilon_{ukt} \end{bmatrix}. \tag{3}$$

The interpretation of the above restrictions is straightforward. Shocks to U.K. output, ε_{ukt}, have no contemporaneous effects on U.S. uncertainty, U.S. output, or Japanese output. Japanese output shocks, ε_{jpt}, have no contemporaneous effects on either U.S. output or U.S. uncertainty. Shocks to U.S., Japanese, and U.K. output have no contemporaneous effect on U.S. uncertainty. While it is plausible that shocks to Japanese and U.K. output have no contemporaneous effects on U.S. uncertainty, it seems unlikely that shocks to U.S. output have no contemporaneous effect on U.S. uncertainty. For this reason we implement two other identification schemes.

First, we simply reverse the ordering of the U_{us} and y_{us} variables. Second, we impose the following Sims-Bernanke (short run) and Blanchard-Quah (1989) (long run) restrictions:

$$\begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \\ e_{4t} \end{bmatrix} = \begin{bmatrix} g_{11} & g_{12} & 0 & 0 \\ * g_{21} & g_{22} & 0 & 0 \\ g_{31} & g_{32} & g_{33} & 0 \\ g_{41} & g_{42} & g_{34} & g_{44} \end{bmatrix} \begin{bmatrix} \varepsilon_{ut} \\ \varepsilon_{ust} \\ \varepsilon_{jpt} \\ \varepsilon_{skt} \end{bmatrix}. \tag{4}$$

The interpretation of the short-run restrictions, $g_{13}=g_{14}=g_{23}=g_{24}=g_{34}=0$, is the same as the interpretation for (3). The long-run restriction we impose is

$$* g_{21} \left[1 - \sum_{i=1}^{p} a_{21_p} \right] = 0 \tag{5}$$

where a_{21p} are the individual coefficients in A_{21} (L). The economic interpretation of this restriction is that uncertainty shocks have no long-run effects on U.S. output. Thus, this identification scheme allows for U.S. uncertainty shocks and U.S. output to contemporaneously affect each other while allowing the possibility that the effects of U.S. uncertainty shocks are propagated internationally.

3.3 Results

For brevity and because the results were not qualitatively different, we only report the results using the first decomposition.[6] Unit root tests indicate that each country's output, as defined in Section 2.1, is stationary, and all measures of uncertainty are found to be stationary in levels. We select the lag length of the VAR according to two criteria. First, we check the adequacy of the model by calculating Ljung-Box Q-statistics for the residuals to ensure the absence of serial correlation. Second, we use the multivariate generalizations of the Akaike Information Criterion (AIC) and Schwartz Bayesian Criterion (SBC) to measure the overall fit of alternative models.

Panels A and B in Figure 2 display the cumulative impulse responses of U.S. output to U.S. uncertainty shocks along with 95% bootstrapped confidence intervals. While the point estimates using the two measures of uncertainty are slightly different, both point estimates display a similar pattern and indicate that U.S. output is negatively affected. Panels A and B suggest that a U.S. uncertainty shock lowers output by 0.6% and 0.4%, respectively. Output is only slightly contemporaneously affected by the uncertainty shock. However, output declines sharply from the first to the sixth month after the shock and then stabilizes. Our results largely confirm those in Bloom (2009), Bloom et al. (2009), and Gilchrist, Sim and Zakrajsek (2009). However, we do not find evidence of "overshooting" in domestic output six months after the shock as reported in Bloom (2009).[7]

The effects of the uncertainty shock on Japanese output are displayed in Figure 2. Panel A suggests a U.S. uncertainty shock has a similar negative effect on Japanese output. The most striking feature of Panel A is the speed at which output declines in Japan in the first two months

[6] All results from the alternative decompositions may be obtained upon request from the authors.
[7] One possible explanation for this difference is Bloom's (2009) use of the HP filter. Cogley and Nason (1995) and Harvey and Jaeger (1993) present evidence that the HP filter may generate spurious business cycle dynamics.

following the shock. Output declines by 0.6% which accounts for most of the decline in Japanese output. Similar to the U.S., output in Japan stops declining approximately six months after the shock. Panel B displays a pattern similar to that in Panel A. While the effects are not always statistically different from zero at the 95% level, the point estimates are all negative. Again, note the speed at which output declines in the first two months after the shock. While it is not as pronounced as in Panel A, Panel B suggests that most of the negative effects on Japanese output from U.S. uncertainty shocks are propagated within the first two months.

The effects on British output are similar to those in Japan and are displayed in Figure 3. Panel A suggests a significant (-0.4%) cumulative decline in British output two years after the shock. As in the U.S. and Japan, British output declines for approximately six months after the shock and then subsequently stabilizes. Again, examination of Panel B offers a similar pattern to Panel A. Most of the negative effects (-0.3%) in Panel B are almost entirely accounted for in the first two months after the shock.

Our results do suggest negative international effects of U.S. uncertainty shocks. The results are somewhat dependent on the uncertainty measure. While the point estimates using both uncertainty measures are consistently negative, the results using the corporate bond spread suggest a more negative impact on output in all three countries. Given that uncertainty shocks do appear to adversely affect foreign output, the next section of the paper examines the effects uncertainty shocks have on foreign exports, foreign inflation, and exchange rates.

U.S. Uncertainty Effects on Foreign Exchange Rates, Exports, and Inflation

Again, we obtained monthly U.K. and Japanese export, exchange rate, and CPI data from the IFS database for the 1970-2010 time period. We estimate the following four-variable VAR for Japan and the U.K.:

$$\begin{bmatrix} U_{us_t} \\ Ex_{i_t} \\ X_{i_t} \\ \pi_{i_t} \end{bmatrix} = \begin{bmatrix} A_{11}(L) & A_{12}(L) & A_{13}(L) & A_{14}(L) \\ A_{21}(L) & A_{22}(L) & A_{23}(L) & A_{24}(L) \\ A_{31}(L) & A_{32}(L) & A_{33}(L) & A_{34}(L) \\ A_{41}(L) & A_{42}(L) & A_{34}(L) & A_{44}(L) \end{bmatrix} \begin{bmatrix} U_{us_{t-1}} \\ Ex_{i_{t-1}} \\ X_{i_{t-1}} \\ \pi_{i_{t-1}} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \\ e_{4t} \end{bmatrix} \tag{6}$$

where U_{us_t} is the measure of uncertainty in the U.S., Ex_{i_t} is the log first difference in the exchange rate, X_{i_t} is the log first difference in foreign exports, π_{i_t} is the foreign inflation rate, A_{ij} (L) are polynomials in the lag operator L, and the e_{it} are regression residuals. To obtain the impulse response functions we simply impose a Choleski decomposition with the above ordering.[8] For brevity and because the results are not qualitatively different, we only report results using the corporate bond spread as the uncertainty measure.

As can be seen in Panel A of Figure 4, the point estimate suggests a U.S uncertainty shock induces a 0.5% contemporaneous depreciation of the dollar relative to the yen. The dollar reaches a trough of -0.75% three months after the shock and then subsequently rebounds. While the point estimates remain persistently below zero, there is no statistically significant effect on the dollar four months after the shock. Examination of Panel B in Figure 4 suggests a much larger effect on Japanese exports. While there is no contemporaneous effect on the level of Japanese exports, there is a statistically significant decline beginning in the first month after the shock and continuing through month five. Export demand subsequently stabilizes, but note that exports remain 3% lower than pre-shock levels after two years. The cumulative effects of the uncertainty shock on Japanese inflation are statistically significant as well. As displayed in Panel C of Figure 4, there is no contemporaneous effect on Japanese inflation. However, beginning in the second month after the shock, Japanese inflation begins a downward trend which continues for two years after the shock. Inflation ends up 0.50% below pre-shock levels. Note that the decline in exports in Figure 4 is very similar to the decline in output displayed in Panel A of

[8] The results were not substantially altered by changing the ordering of the last three variables.

Figure 2. The negative effects of the shock on output and exports stabilize approximately six months after the U.S. uncertainty shock.

Panel A of Figure 5 displays the impulse responses of the dollar/pound exchange rate to the U.S. uncertainty shock. The depreciation of the U.S. dollar in this case is similar to the depreciation of the dollar against the yen. While the point estimates suggest a -0.25% contemporaneous depreciation of the dollar relative to the pound, it is not statistically significant. The dollar reaches a trough of -0.75% six months after the shock. While the point estimates remain persistently below zero, there is no statistically significant effect on the dollar seven months after the shock. British exports also react much like Japanese exports. There is no contemporaneous effect on British exports, but exports begin a statistically significant downward trend beginning one month after the shock. After two years, British exports are -1.5% below pre-shock levels. The effects on British inflation display a pattern similar to Japanese inflation. British inflation declines approximately 0.6% two years after the U.S. uncertainty shock.

Note that the international effects of U.S. uncertainty shocks appear consistent with a demand shock in an open-economy IS/LM model with sticky prices. Domestic uncertainty shocks lower domestic investment (as in Bloom (2009), Bloom et al. (2009), and Gilchrist, Sim and Zakrajsek (2009)) relative to savings due to a “wait and see” attitude among economic actors and shift the domestic IS curve leftward. This lowers the equilibrium interest rate and causes the domestic currency to depreciate. Lower domestic output and a weaker domestic currency induce a decline in foreign exports causing foreign output and inflation to decline. In short, our results suggest U.S. uncertainty shocks cause a leftward shift in the foreign economies’ IS curves.

3.4 Historical Decompositions

Our findings suggest U.S. uncertainty shocks significantly affect foreign economies. In this section, we seek to answer the following question: did U.S. uncertainty shocks contribute to the fluctuations in foreign economies' output during with the recent financial crisis? To answer this question we forecast each equation in our VAR without any shocks. Then we reforecast the equations adding each shock one at a time. Our methodology is similar to Cover (2011), and Figure 6 shows the results.[9] The dotted line in Panel A shows the level of uncertainty assuming that the only shock is the uncertainty shock, and the dashed line assumes that the only shocks are the uncertainty shock and the shock to U.S. output. Finally, the thick solid line consists of all shocks and is shown as the actual value of uncertainty. Panel A reveals that most of the increase in uncertainty is the result of the uncertainty shock.

Panels B, C, and D show the historical decompositions for the U.S., Japan, and the U.K., respectively during the recent financial crisis. The thin solid line in each panel represents forecasts with all of the shocks turned off. We cumulatively add the forecasts each period to obtain the forecast values. The thick solid line in each Panel is the actual value of industrial production while the dotted and dashed lines represent contributions of the U.S. uncertainty shock and U.S. output shock, respectively. Hence, the distance between the U.S. output shock and the realized actual values represents the portion of the forecast error explained by the combination of Japanese and U.K. output shocks, and the distance between the forecast and the uncertainty shock represents the portion of the forecast error that is explained by the uncertainty shock. In each Panel, uncertainty explains a large portion of the variation in output for each country during the recent financial crisis. In Panel B, uncertainty explains roughly the same amount of the forecast error as U.S. output. However, for each of the foreign economies,

[9] The results shown use the corporate bond spread as the uncertainty measure. The results are not substantially different using the S&P 500 index as the uncertainty measure.

uncertainty explains more of the forecast error than U.S. output and roughly the same as the foreign economies' output shock. This would suggest that U.S. uncertainty played a significant role in reducing foreign countries' output during the recent financial crisis.

3.5 Conclusion

Our results suggest that domestic uncertainty shocks appear to be a mechanism by which business cycles may be transmitted internationally. U.S. uncertainty shocks have results consistent with an adverse, open-economy demand shock. Point estimates suggest that uncertainty shocks (1) reduce foreign output, (2) induce a depreciation of the domestic currency, (3) reduce foreign exports, and (4) slow foreign inflation. We also find using historical decompositions that uncertainty shocks during the recent financial crisis explain an important part of the declines in foreign economies' output. Further research is needed to understand other channels through which domestic uncertainty shocks may affect foreign economies.

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Figure 3.1. Time Series Plot of Variables

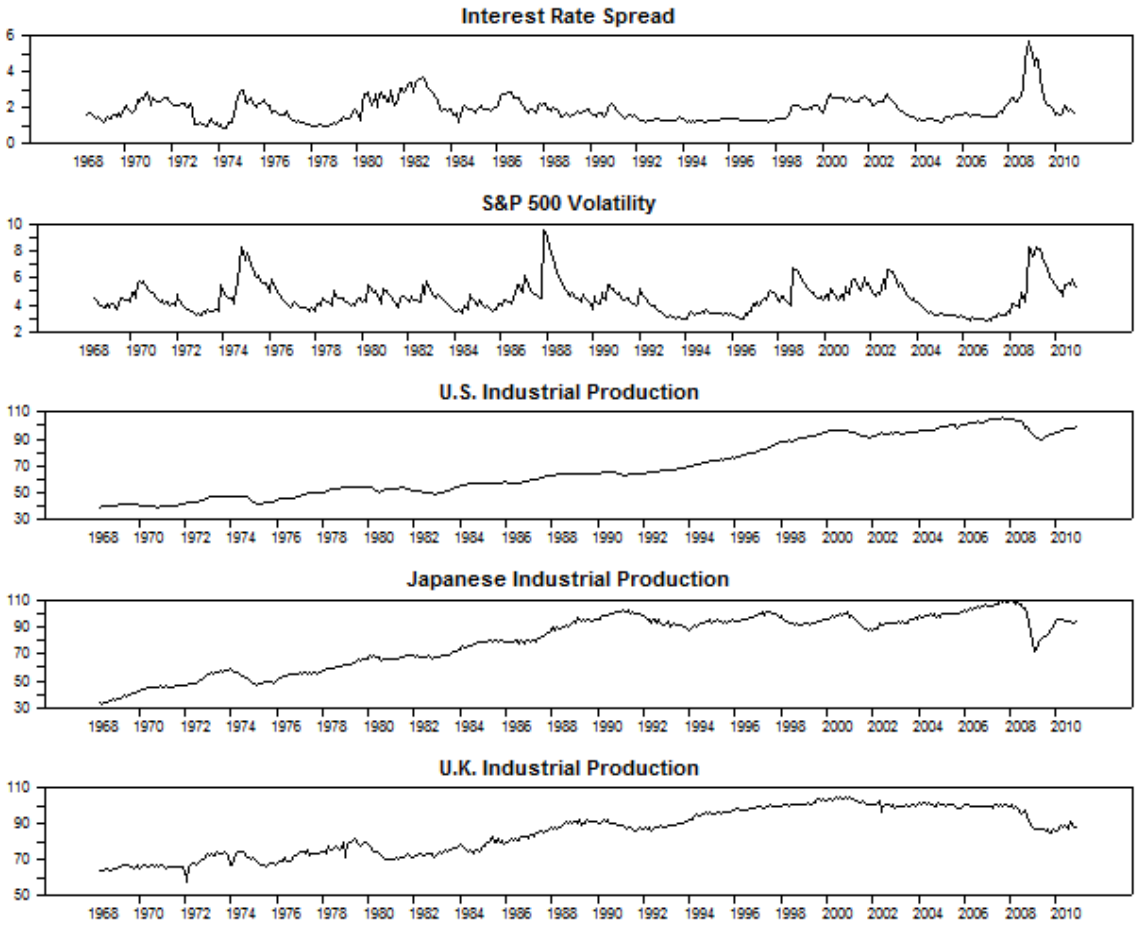
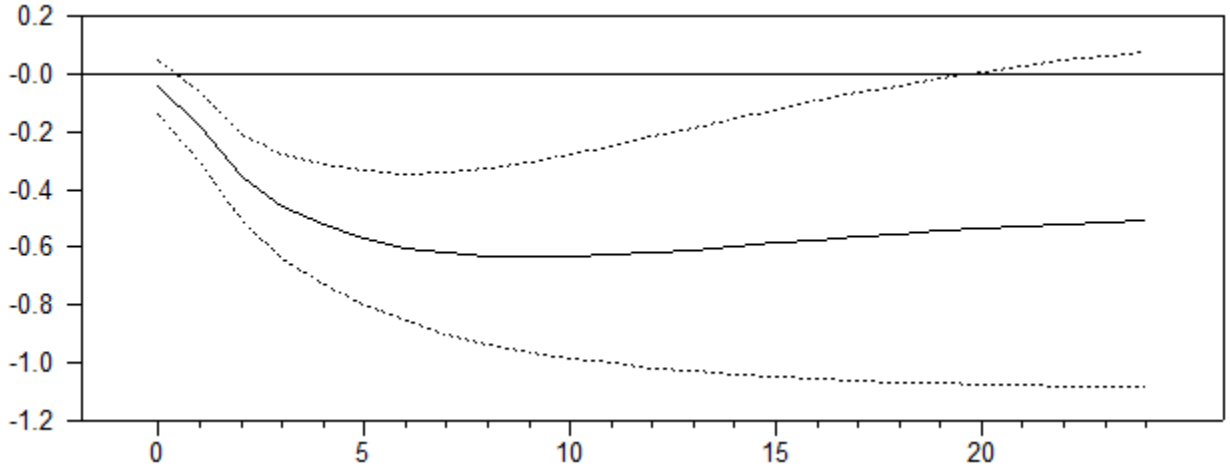


Figure 3.2. U.S. Output Response to a U.S. Uncertainty Shock

Panel A: U.S. Uncertainty Measure (Bond Spread)



Panel B: U.S. Uncertainty Measure (S&P 500 Volatility)

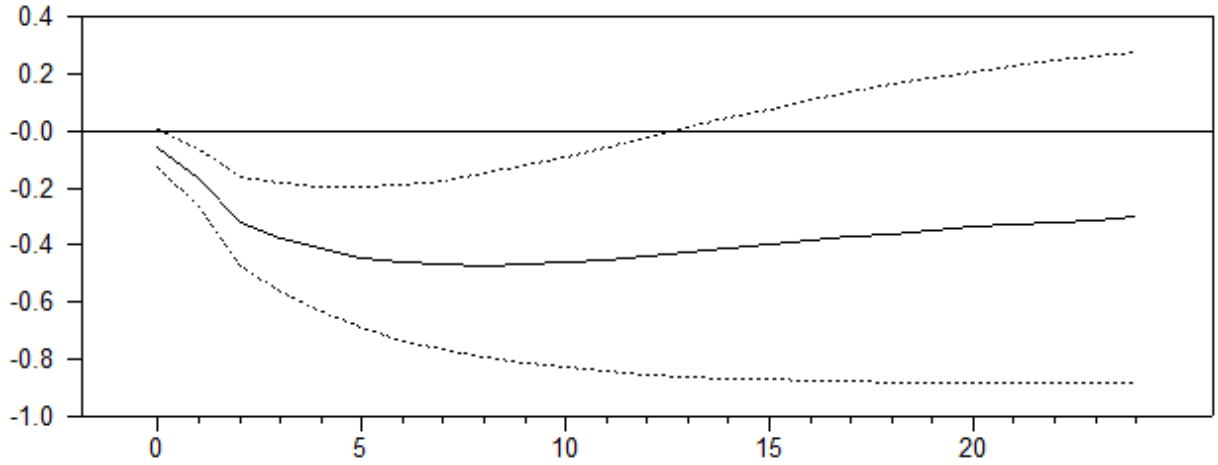
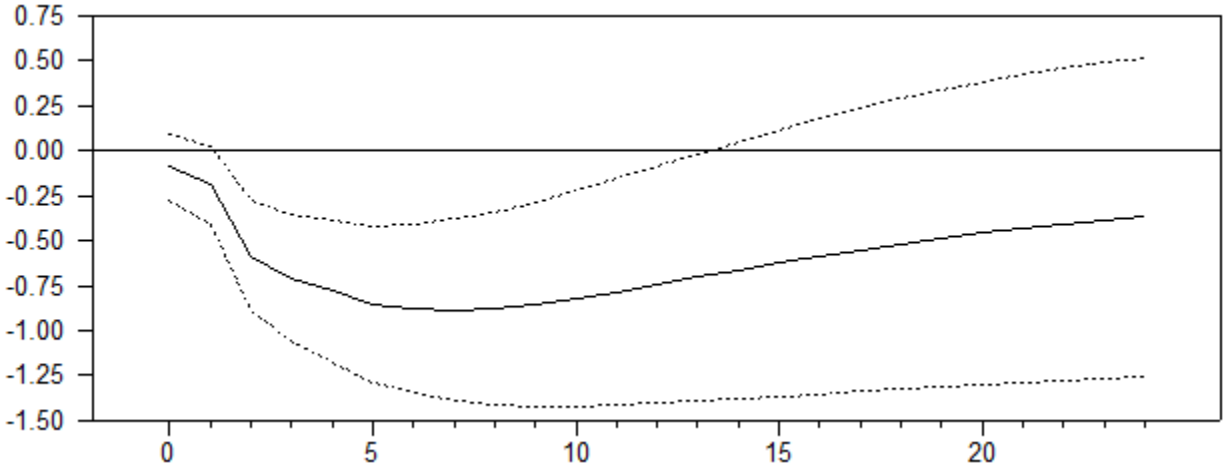


Figure 3.2 – The above displays the cumulative impulse response functions of U.S. output to a one standard deviation shock to U.S. uncertainty along with 95% bootstrapped confidence intervals.

Figure 3.3. Japanese Output Response to a U.S. Uncertainty Shock

Panel A: U.S. Uncertainty Measure (Bond Spread)



Panel B: U.S. Uncertainty Measure (S&P 500 Volatility)

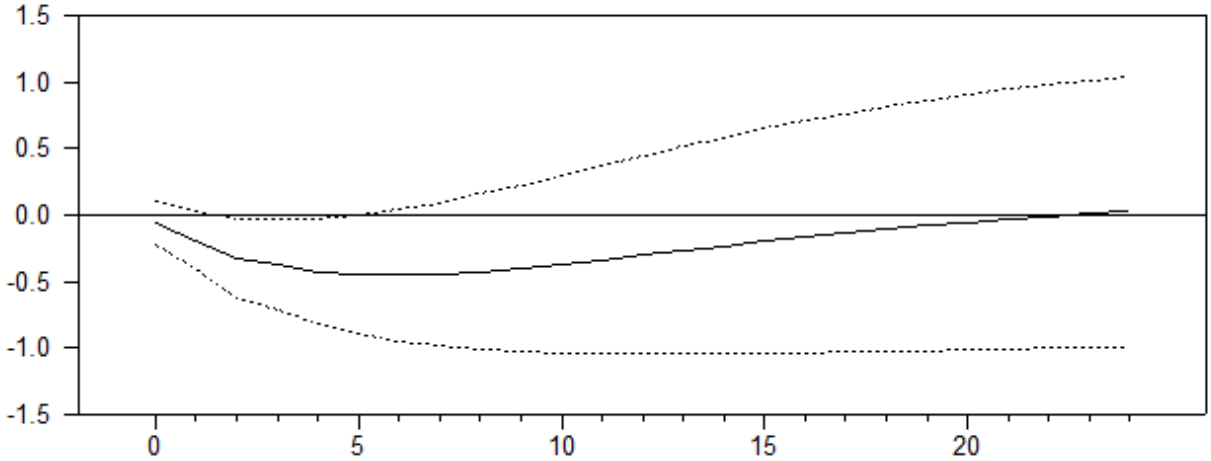
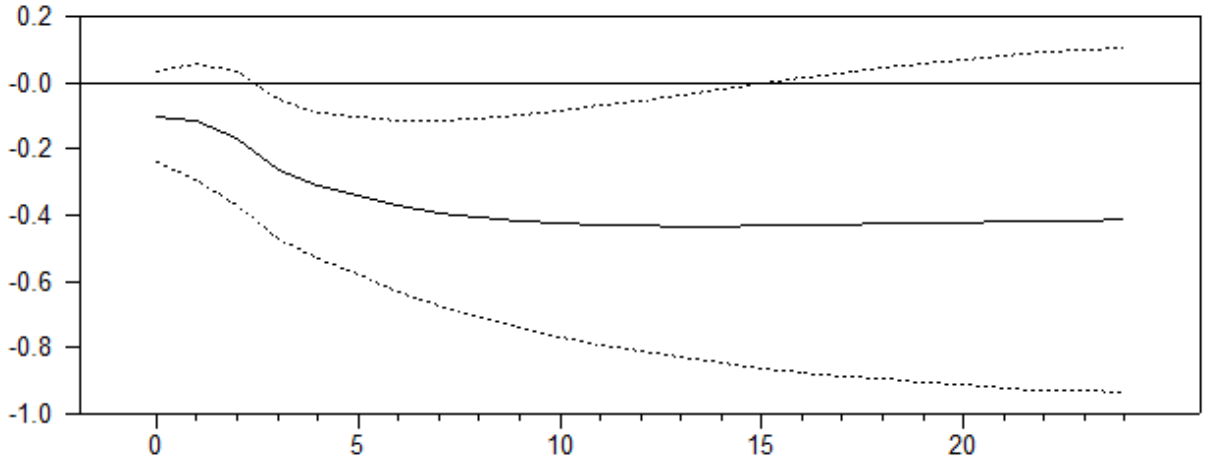


Figure 3.3 – The above displays the cumulative impulse response functions of Japanese output to a one standard deviation shock to U.S. uncertainty along with 95% bootstrapped confidence intervals.

Figure 3.4. U.K Output Response to a U.S. Uncertainty Shock

Panel A: U.S. Uncertainty Measure (Bond Spread)



Panel B: U.S. Uncertainty Measure (S&P 500 Volatility)

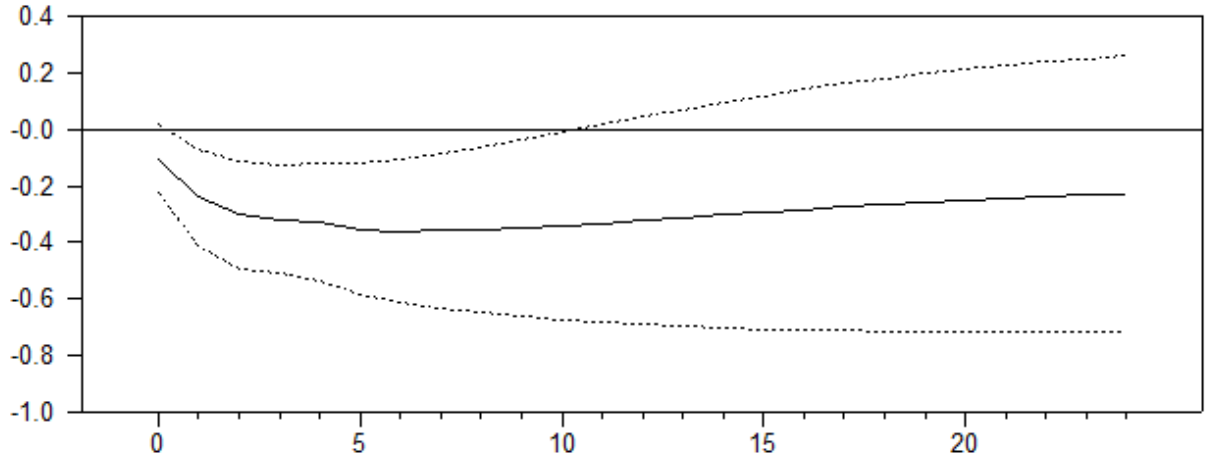
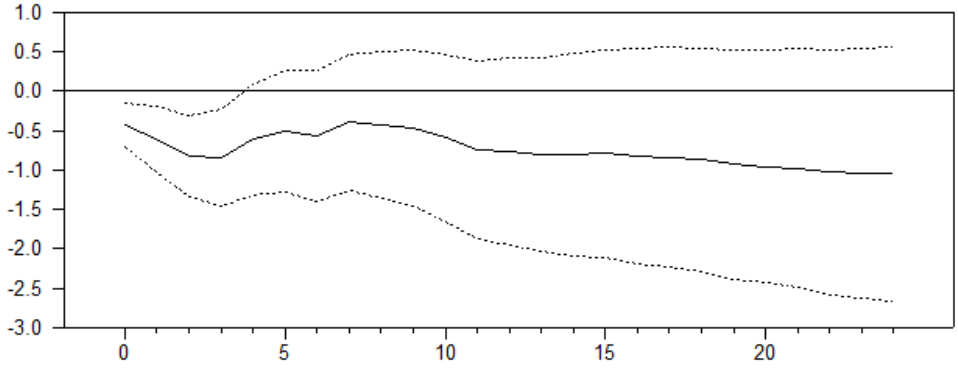


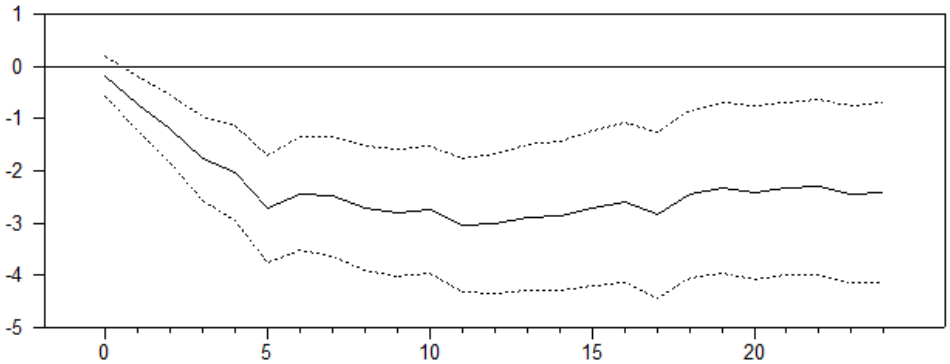
Figure 3.4 – The above displays the cumulative impulse response functions of British output to a one standard deviation shock to U.S. uncertainty along with 95% bootstrapped confidence intervals.

Figure 3.5. Japanese Responses to a U.S. Uncertainty Shock

Panel A: Dollar/Yen Exchange Rate



Panel B: Japanese Exports



Panel C: Japanese Inflation

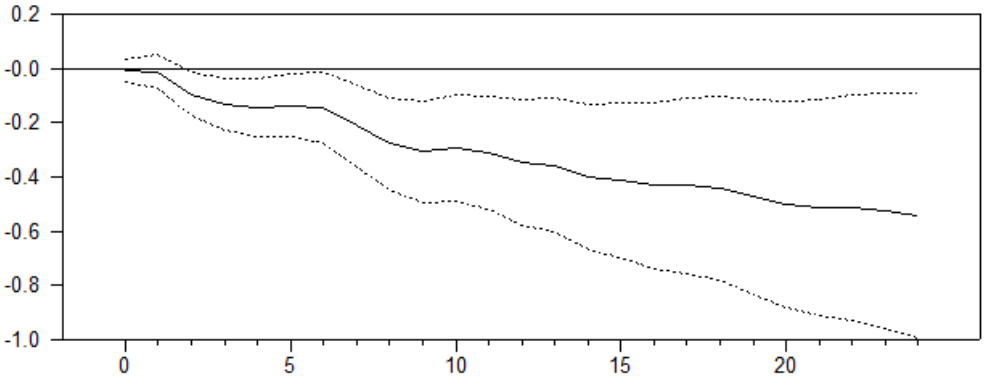
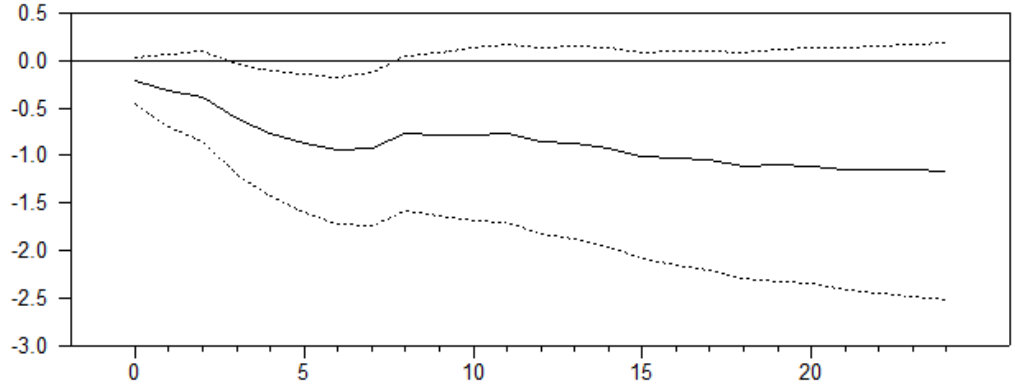


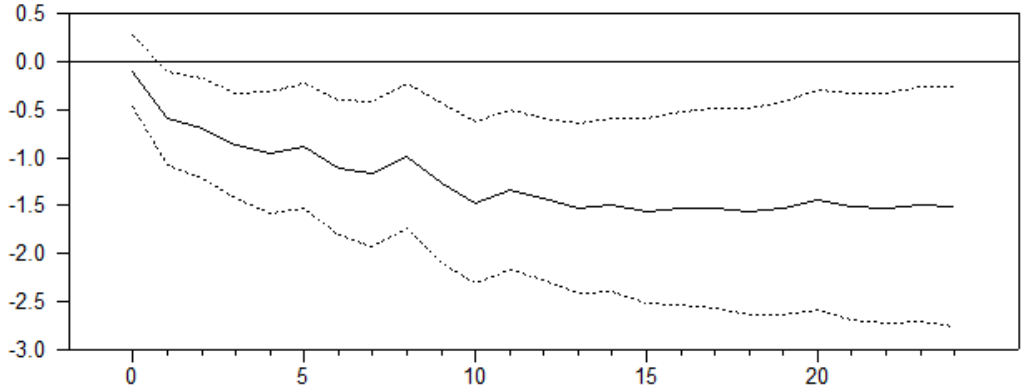
Figure 3.5 – The above displays the cumulative impulse responses of Japanese exports, dollar/yen exchange rate, and Japanese inflation to a one standard deviation shock to U.S. uncertainty as measured by the difference between 30-year Baa corporate bond and the 30-year Treasury bond with bootstrapped 95% confidence intervals.

Figure 3.6. U.K. Responses to a U.S. Uncertainty Shock

Panel A: Dollar/Pound Exchange Rate



Panel B: U.K. Exports



Panel C: UK Inflation

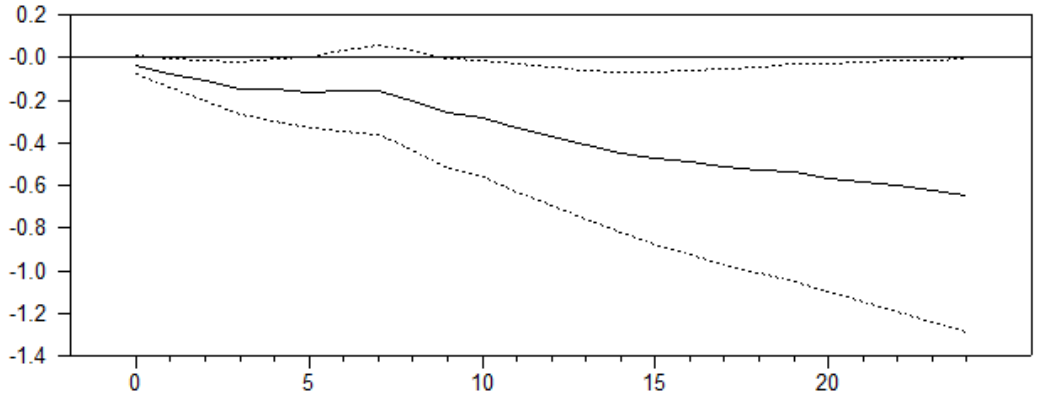
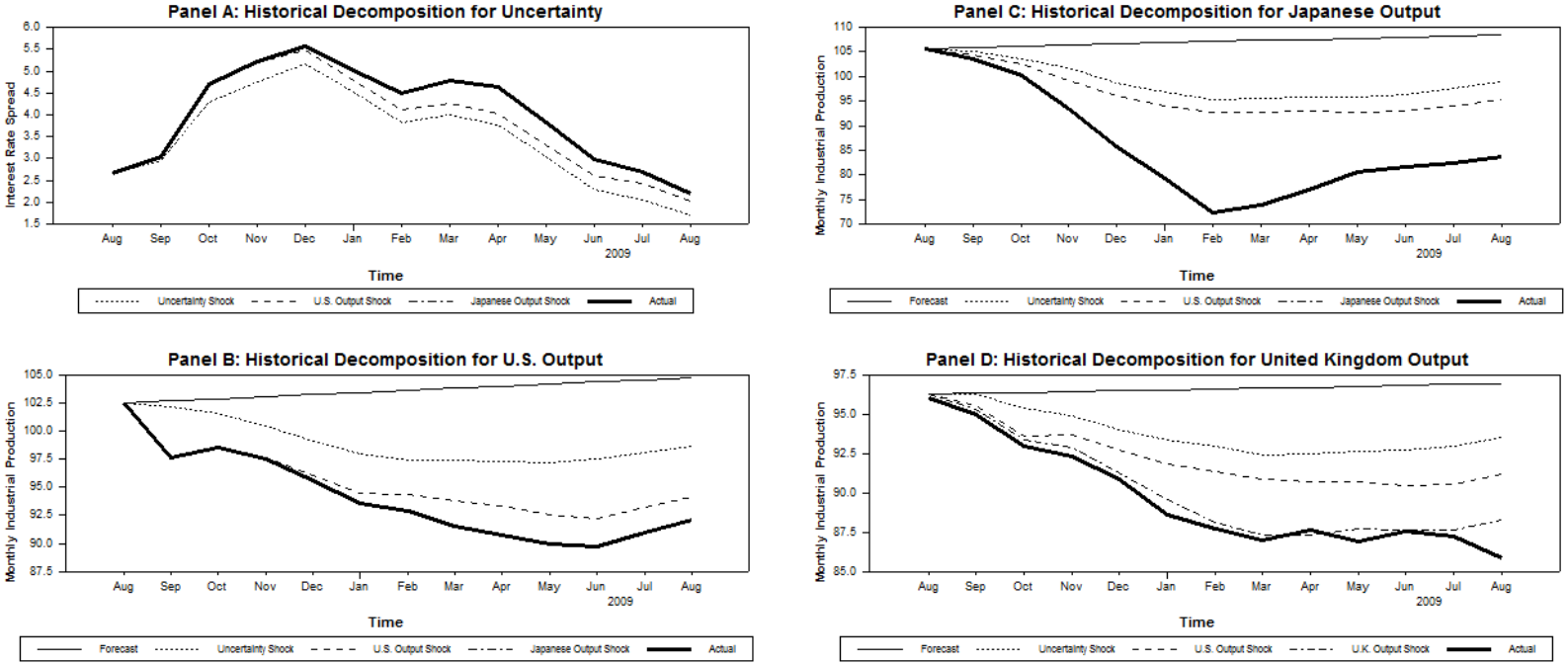


Figure 3.6 – The above displays the cumulative impulse responses of British exports, dollar/pound exchange rate, and Bristish inflation to a one standard deviation shock to U.S. uncertainty as measured by the difference between 30-year Baa corporate bond and the 30-year Treasury bond with bootstrapped 95% confidence intervals.

Figure 3.7. Historical Decompositions



CHAPTER 4

THE ASYMMETRIC EFFECTS OF UNCERTAINTY ON MACROECONOMIC ACTIVITY

4.1 Introduction

The large trough and subsequent, slow recovery from the Great Recession of 2008–2009 has led to a 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 potentially cause recessions by incentivizing firms to delay investment and employment decisions during times of high uncertainty. More recently, Bloom (2009) and Bloom et al. (2012) develop simulation models in which positive uncertainty shocks lead to temporary reductions in investment and employment. Similarly, Gilchrist, Sim, and Zakrajsek (2010) 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 increases in uncertainty result in agency problems which 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 lead to as much as a 3.2 percent 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 Bloom (2009), Eisner and Strotz (1963), Lucas and Prescott (1971), and Lucas (1981), 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.[10] Thus, we anticipate that uncertainty increases are transmitted to the economy faster 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. 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

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

suggests that the region of inaction is actually a smooth process. To capture this type of behavior, we employ a 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 which 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 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 decreases in response to uncertainty whereas banks increase their cash holdings as uncertainty rises. Section 7 concludes.

4.2 Data and Pretesting for Nonlinearity

There is no consensus of 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. 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 HP mean.[11] 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. 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.[12] Instead, to avoid any controversy involved with the use of the HP filter, our output measure is the log difference of monthly industrial production.[13] All of our data series were obtained from FREDII, and the transformations used for each are described in the Appendix.

Before proceeding to estimate each series as a nonlinear process, it seems reasonable to pretest for nonlinearity in order to determine if each series displays some sort of nonlinear adjustment. Toward this end, we subject each series to a battery of tests for nonlinearity. Note

[11] As a robustness check, Bloom (2009) also uses the entire HP detrended volatility series, and the results are virtually unchanged with output declining quickly then overshooting.
[12] 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 is 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.
[13] Nevertheless, using the HP filter on our data yields results that are not very different from those reported here.

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 since it is not possible to directly perform an LM test for the presence of STAR behavior. Consider the following simple LSTAR model:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \theta(\beta_0 + \beta_1 y_{t-1}) + \varepsilon_t \tag{1}$$

where $\theta = [1 + \exp(-\gamma(y_{t-1} - c))]^{-1}$.

The null hypothesis in an LM test for nonlinearity (i.e., $\gamma = 0$) suffers from the so-called Davies problem since β_0, β_1, and c are unidentified under the null of $\gamma = 0$. Instead, Teräsverta (1994) rewrites θ as

$$\theta = [1 + \exp(-\gamma(y_{t-1} - c))]^{-1} \equiv [1 + \exp(-g_{t-1})]^{-1},$$

so $g_{t-1} = \gamma(y_{t-1} - c)$ and takes a third-order Taylor series approximation of θ to perform a general test for STAR behavior. The test involves multiplying the regressors in (1) by the approximation for θ and then regressing all such terms on the residuals of the linear model. Hence, estimate

$$\varepsilon_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + a_{11} y_{t-1} y_{t-d} + a_{12} y_{t-2} y_{t-d} + a_{21} y_{t-1} y_{t-d}^2 + \ldots \quad .$$

The test for nonlinearity entails the restriction that all values of $a_{ij} = 0$.

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.

Table 1 reports the results from the three nonlinear tests for each of the macroeconomic variables used in our study.[14] As shown in the table, when we applied Hansen's bootstrap threshold test to industrial production, we obtained an *F*-statistic of 4.72 which is significant at better than the 95 percent level. Notice that each variable has at least two tests allowing us to reject the null hypothesis of linearity at better than the 90 percent confidence level. This suggests that nonlinear models are likely to capture the time series dynamics of these macroeconomic variables more accurately than linear models. However, the particular form of nonlinearity cannot be pinned down by the nonlinear tests. Section 3 discusses our particular nonlinear framework.

Given that our macroeconomic variables should be modeled using a nonlinear framework, we proceed to test our uncertainty measure for nonlinearity. 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:

$$\Delta \ln(x_t) = c + \varepsilon_{1t} \tag{2}$$

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

where x_t is the value of the S&P 500, c is a constant, $\varepsilon_{1t} \sim N(0, h_t)$, and h_t is a GARCH(1,1) process such that the standardized residuals $\{s_t\}$ can be written as

$$s_t = \varepsilon_{1t} / \sqrt{h_t}.$$

Then let D_{t-1}^{-} be a dummy variable equal to 1 if $\hat{\varepsilon}_{1t-1} < 0$ and equal to zero if $\hat{\varepsilon}_{1t-1} \geq 0$. 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 s_{t-1} times D_{t-1}^{-} (D_{t-1}^{+}) on the estimated squared residuals.

Table 2 reports the results of Engle and Ng's (1993) tests for asymmetry. The simple GARCH(1,1) model, shown in the first row of the table, is given by h_t = 0.00009 + $0.11\varepsilon_{t-1}^2 + 0.84h_{t-1}$. 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. Note that the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) from the EGARCH model are both smaller than those from the simple GARCH(1,1) model. Therefore, we estimate the following EGARCH(1,1) model as our measure of uncertainty:

$$\log h_t = \underset{(-3.02)}{-0.82} + \underset{(3.48)}{0.21}\left|\varepsilon_{1t-1}\right| / \sqrt{h_{t-1}} + \underset{(23.15)}{0.90}\log h_{t-1} - \underset{(-4.21)}{0.11}\varepsilon_{1t-1} / \sqrt{h_{t-1}}. \tag{3}$$

The key feature of (3) is the negative coefficient on $\varepsilon_{1t-1}/\sqrt{h_{t-1}}$ which guarantees 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 (3) along with monthly U.S. industrial production. Recessions, as defined by the NBER, are represented by shaded areas in Figure 1. While it does appear that positive increases in uncertainty often accompany decreases in output, this is not always the case. The most obvious 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.

Our final pretest involves a slight modification to the Teräsverta (1994) procedure described above. In Section 3, we model industrial production as an LSTAR process with our measure of uncertainty, h_t, as the transition variable. Thus, it is possible to test the null hypothesis of linearity directly against the alternative of an LSTAR model with h_t as the transition variable. Consider the following LSTAR model:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \theta(\beta_0 + \beta_1 y_{t-1}) + \varepsilon_t \tag{4}$$

where $\theta = [1 + \exp(-\gamma(h_t - c))]^{-1}$ and h_t is the measure of uncertainty from (3). Rewrite θ as

$$\theta = [1+\exp(-\gamma(h_t - c))]^{-1} \equiv [1+\exp(-g_{t-1})]^{-1},$$

so $g_{t-1} = \gamma(h_t - c)$ and take a third-order Taylor series approximation of θ to perform the test for STAR behavior. Our modified Teräsverta (1994) procedure involves multiplying the regressors in (4) by our new approximation for θ and then regressing all such terms on the residuals of the linear model. The test for nonlinearity entails the restriction that all values of the Taylor series approximation are equal to zero. After carrying out this procedure, we obtain an F-statistic of

3.92 which is significant at better than the 99 percent level. Thus, we reject the null hypothesis of linearity and accept the alternative nonlinear model discussed more fully in Section 3.

4.3 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 Section 3, we compare a linear model of the industrial production series to our nonlinear specification. For the linear model, the BIC selects a model with two lags.[15] Let y_t denote the logarithmic change in monthly industrial production so that:

$$y_t = \underset{(3.91)}{0.0013} + \underset{(9.88)}{0.36} y_{t-1} + \underset{(3.27)}{0.12} y_{t-2} + \varepsilon_{2t} \tag{5}$$

aic = -2129.1 bic = -2115.3

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 4 and 8 lags of the standardized residual autocorrelations have *prob*-values of 0.21 and 0.25, respectively. The linear model represented by (5) 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 to 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.

In order to allow uncertainty shocks to have differential effects on industrial production, we also 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 (4), γ is

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

sufficiently large, the LSTAR and threshold specifications are essentially identical. Consider the following LSTAR model of industrial production:[16, 17]

$$\hat{y}_t = 0.003 + 0.28 y_{t-1} + (-0.005 + 0.35 y_{t-1})[1 + \exp(-6.146(h_t - 2.155))]^{-1} \tag{6}$$

(7.13) (8.26) (-5.97) (5.61)

aic = -2145.7 bic = -2118.1

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

Notice the transition variable in (6) is the contemporaneous value of uncertainty from (3) as opposed to the lagged value of industrial production. Also note, 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 $\theta = [1 + \exp(-6.146(h_t - 2.155))]^{-1}$ 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 (6), it should be clear that when θ = 0 (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 θ = 1 (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.

4.4 Historical Decompositions

[16] See Section 5.2 for analysis using a nonlinear VAR model and Section 6 for model estimates of other important macroeconomic measures and different measures of uncertainty.

[17] A t-test for γ is not reported since the parameters in the LSTAR model are undefined when γ = 0. Likewise, the variance is always positive. Therefore, a t-test for c = 0 is also not reported.

In order 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 equal to the average value over the 1990s. Therefore, the h_t series is set equal to 1.48 and $\theta \approx 0.015$ 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.[18] 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 percent 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 $\theta \approx 1$). 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 percent as compared to the actual value.

4.5 Impulse Response Functions

Koop, Pesaran, and Potter (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 linearity property (e.g., a

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

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, since the initial state of the system, as well as the size, sign, and subsequent values of the shocks, affect the responses.

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 (2) 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 with replacement the residuals from a uniform distribution and use these residuals to produce { h^*_t } = h^*_t through h^*_{t+24}. These { h^*_t } values are substituted into the LSTAR model given by (6) to generate the recursive values of y^*_t through y^*_{t+24}. For each particular history, we repeat the process 1000 times and obtain the mean values of the impulse responses along with the 95 percent confidence intervals.

Panel C of Figure 2 shows the impulse responses of a permanent positive and negative uncertainty shock 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 its long-run equilibrium from the linear model, equation (5). Thus, θ = ½ in period one before the uncertainty shocks and industrial production is equal to 0.013 / (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. The uncertainty shocks in Panel C of Figure 2 are permanent positive and negative one-standard-deviation shocks from the residuals of (2). Hence, for a permanent positive (negative) uncertainty shock, the value of uncertainty in every period is determined by setting the residuals

$\varepsilon^*_{1t+1}, \varepsilon^*_{1t+2}, ..., \varepsilon^*_{1t+12}$ equal to a minus (plus) one-standard-deviation innovation in the residuals of (2). As shown by the reflection of the permanent 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 permanent positive uncertainty shock and rises only from 0.0025 to 0.00417 for the permanent negative uncertainty shock.[19] Also, consistent with our historical decompositions, permanent high values of uncertainty lead to permanent decreases in output, and permanent low values of uncertainty lead to permanent 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 1000 times. The figure shows the mean values of industrial production along with 95 percent confidence intervals. Initially, a positive 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. While the 2008:12 uncertainty shock actually had a large negative effect on output for that period, our counterfactual analysis shows that it would have little effect if it had occurred

[19] Table 3 reports these same results in a different manner. 0.0025 is the long-run equilibrium from the linear model of industrial production, -0.0054 is the high uncertainty regime equilibrium, and 0.00417 is the low uncertainty regime equilibrium.

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 consequence of 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 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 pre-shock 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 pre-shock 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 reasonably sized uncertainty shocks—even as much as two-standard-deviations—occurring during a favorable state of economic activity have little effect.

An alternative methodology to estimate the nonlinear effects of uncertainty on output is to estimate the growth rate of industrial production (i.e., y_t) and uncertainty as a simultaneous

system. Since the conditional variance of the S&P 500 is not directly observable, we use implied volatility based on the Chicago Board of Options Exchange VXO index as our measure of uncertainty. This index is available from 1986 onward. 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:

$$y_t = \underset{(6.93)}{0.0033} - \underset{(-1.80)}{0.15} y_{t-1} + (\underset{(-5.20)}{-0.0039} + \underset{(6.62)}{0.76} y_{t-1})[1+\exp(-4.36(vxo_{t-1} - 23.23))]^{-1} + \varepsilon_{3t}.$$

$$vxo_t = \underset{(4.54)}{3.55} + \underset{(25.24)}{0.83} vxo_{t-1} + \underset{(0.70)}{30.45} y_{t-1} + \varepsilon_{4t}.$$

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 the coefficient on output is insignificant. In a sense the *t*-statistic in this case acts like a Granger causality test. Thus, an 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 θ against our uncertainty measure where $\theta = [1+\exp(-4.36(vxo_{t-1} - 23.23))]^{-1}$. The figure shows high values of uncertainty produce θ values equal to one, low values of uncertainty produce θ values equal to zero, and intermediate values of uncertainty produce θ values between zero and one. When $\theta = 0$ 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 $\theta = 1$ 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 two-step estimation, high values of uncertainty decrease output and are more persistent than low values of uncertainty.

4.6 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 4. In each case, uncertainty is the transition variable in the most appropriate LSTAR model for each sector. As should be clear from (1), 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 change in output is causing uncertainty to change, it is unlikely that uncertainty would affect each production and financial flow variable similarly.

Since 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 $\theta = 1$ and the low uncertainty regime equilibrium is found by setting $\theta = 0$ in each of the LSTAR models reported in Table 4. For example, the last column of Table 4 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 $\theta = 1$, 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 long-run equilibrium from 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 long-run equilibrium from the linear model are greater than the differences between the low uncertainty regime and the long-run equilibrium 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.[20] 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.

Given the recent claims that banks have been hoarding cash and frustrating the Federal Reserve's efforts to lower interest rates, 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:

$$\hat{y}_t = \underset{(6.66)}{0.0031} + \underset{(20.87)}{0.61} y_{t-1} + (\underset{(-3.52)}{-0.0026} + \underset{(1.02)}{0.08} y_{t-1})[1+\exp(-3.23(h_t - 2.103))]^{-1} \tag{6}$$

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

[20] This can be seen graphically in Figure 2 Panel C and Figure 7 Panel C.

θ 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 (i.e., θ is close to zero), the skeleton of (6) indicates that the long−run equilibrium value of consumer credit is 0.00795 = 0.0031/(1 – 0.61). However, when uncertainty is high (i.e., θ is close to unity), 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.

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. Similar to our aforementioned historical decompositions, during this first period we set the value of uncertainty equal to its average value of for the 1990s (i.e., h_t = 1.48 and $\theta \approx 0.015$ 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 to 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 percent 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 $\theta \approx 1$). Then we set the initial condition y_t equal to the actual value for 2010:M6 and iterate forward. As shown in Figure 7, if the uncertainty level had remained constant at its average level for the financial crisis, consumer credit would have grown at a slower rate. Note that over the two year period counterfactual

consumer credit would have been approximately 5 percent 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 4, 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 banks continue to hoard cash and restrict the amount of consumer credit.

Panel C of Figure 7 shows the impulse responses of a permanent positive and a permanent negative uncertainty shock on 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 its long-run equilibrium from the linear model [i.e., row 4 in Table 3]. Thus, $\theta = ½$ in period one before the uncertainty shocks and consumer credit is equal to 0.00633. For a permanent positive (negative) uncertainty shock, the value of uncertainty in every period is determined by setting the residuals $\varepsilon^*_{1t+1}, \varepsilon^*_{1t+2}, ..., \varepsilon^*_{1t+12}$ equal to a minus (plus) one-standard-deviation innovation of the residuals in (2). As illustrated by the reflection of the permanent 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 permanent positive uncertainty shock and rises only from 0.0063 to 0.00795 for the permanent negative uncertainty shock.

We investigate how different sized shocks affect consumer credit were they all to occur in 2008:12. In Panel A of Figure 8, the solid, dotted, and dashed lines show bootstrapped mean values of +2, +1, and –1-standard-deviation temporary shocks on 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 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 on 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.

4.7 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 we 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, 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.

Since 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 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.

Data Appendix
In this appendix, we describe the data for our measures of uncertainty and macroeconomic variables.

A.1 – Output Data
We use three different measures of output and three financial measures to investigate the effects of uncertainty. All of the measures come from the Federal Reserve Economic Database (FRED).

Industrial Production
Industrial production is the log difference of monthly industrial production from 1950:1-2012:1.

Durable Goods
Durable goods is the log difference in monthly durable consumer goods taken from industrial production from 1950:1-2012:1.

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

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

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

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

A.2 – Uncertainty Data
We use the following four variables as our measures of uncertainty.

Conditional Variance of the S&P 500
We use an EGARCH(1,1) model as our estimate of the conditional variance of the S&P 500. The S&P 500 is obtained monthly from 1950:1 - 2012:1.

Interest Rate Spread
For our second measure of uncertainty we follow Gilchrist, Sim, and Zakrajsek (2009) 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. This interest rate spread runs from 1953:4 - 2012:1.

Business Outlook Survey
Our next measure comes from Bachmann, Elstner, and Sims (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 using the following formula:

$$uncertainty_t = sqrt(Frac_t(increase) + Frac_t(decrease) - (Frac_t(increase) - Frac_t(decrease))^2)$$

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. The data runs from 1968:5 - 2012:1.

Uncertainty Index

Our final measure of uncertainty is the monthly, policy-related uncertainty index by 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 next component is the number of federal tax code provisions set to expire in future years, and the final is the extent of disagreement between economic forecasters over future federal government purchases and consumer price index (CPI) levels.

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Table 4.1. Nonlinearity Tests

Nonlinear Tests[1]	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***
Test of Threshold Effect	4.72**	15.10***	12.53***	12.03***	5.32***	5.18***

Note: The table reports *F*-statistics for each of the above nonlinear tests.
* Denotes statistical significance at the 90% level.
** Denotes statistical significance at the 95% level.
*** Denotes statistical significance at the 99% level.
[1]Under the null hypothesis, each process is linear.

Table 4.2. – Testing for EGARCH Behavior in Uncertainty

GARCH(1,1) Model	$h_t = \underset{(2.86)}{0.00009} + \underset{(4.55)}{0.11}\varepsilon_{t-1}^2 + \underset{(29.98)}{0.84}h_{t-1}$ aic = -2642.18 bic = -2623.74
Engle and Ng (1993) Tests	
Sign Bias Test	$s_t^2 = \underset{(7.16)}{0.71} + \underset{(4.22)}{0.61}D_{t-1}^- + v_t$
Negative Size Bias Test	$s_t^2 = \underset{(10.65)}{0.91} - \underset{(-2.10)}{0.23}D_{t-1}^- s_{t-1} + v_t$
Positive Size Bias Test	$s_t^2 = \underset{(13.45)}{1.20} - \underset{(-3.93)}{0.55}D_{t-1}^+ s_{t-1} + v_t$
All Three Tests	$s_t^2 = \underset{(5.44)}{0.91} + \underset{(2.20)}{0.51}D_{t-1}^- + \underset{(0.75)}{0.11}D_{t-1}^- s_{t-1} - \underset{(-1.46)}{0.28}D_{t-1}^+ s_{t-1} + v_t$ Chi-Squared (3) = 20.09 with significance level 0.00016
EGARCH (1,1) Model	$\log h_t = \underset{(-3.02)}{-0.82} + \underset{(3.48)}{0.21}\lvert\varepsilon_{t-1}\rvert / \sqrt{h_{t-1}} + \underset{(23.15)}{0.90}\log h_{t-1} - \underset{(-4.21)}{0.11}\varepsilon_{t-1} / \sqrt{h_{t-1}}.$ aic = -2658.68 bic = -2635.62

Table 4.3. Long-run Equilibrium for Positive and Negative Shocks

	Lags	Long-run Equilibrium	High Uncertainty Regime Equilibrium	Low Uncertainty Regime Equilibrium	Difference Between High and Long-run Equilibrium	Difference Between Low and Long-run Equilibrium
Linear Models						
Industrial Production	2	0.0025				
Durable Goods	1	0.00266				
Employment	3	0.0014				
Consumer Credit	3	0.00633				
Bank Loans	5	0.0062				
Bank Cash	1	0.00632				
LSTAR Models						
S&P Var - Ind. Prod.			-0.0054	0.00417	**-0.0079**	0.00167
S&P Var - CC			0.0016	0.00795	**-0.00473**	0.00162
S&P Var - Emp.			0.00	0.0021	**-0.0014**	0.0007
BOS - Ind. Prod.			-0.0015	0.0043	**-0.004**	0.0018
BOS - Durables			-0.0187	0.0087	**-0.02136**	0.00604
BOS - CC			0.0054	0.0075	-0.00093	**0.00117**
Index - Ind. Prod.			0.00	0.0028	**-0.0025**	0.0003
Index - Loans			0.00	0.0083	**-0.0062**	0.0021
Index - CC			0.00105	0.0072	**-0.00528**	0.00087
Int. Spread - Cash			0.1137	0.00397	**0.10738**	-0.00235

Note: The number of lags for the linear models is selected by minimizing the BIC. Each of the equilibriums for the LSTAR models are obtained from the coefficient estimates in Table 4. The numbers in bold indicate whether the absolute value of the difference between the high uncertainty equilibrium and long-run equilibrium or the difference between the low uncertainty equilibrium and the long-run equilibrium is greater.

Table 4.4. Alternate Measures of Uncertainty and Other Important Macroeconomic Variables

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

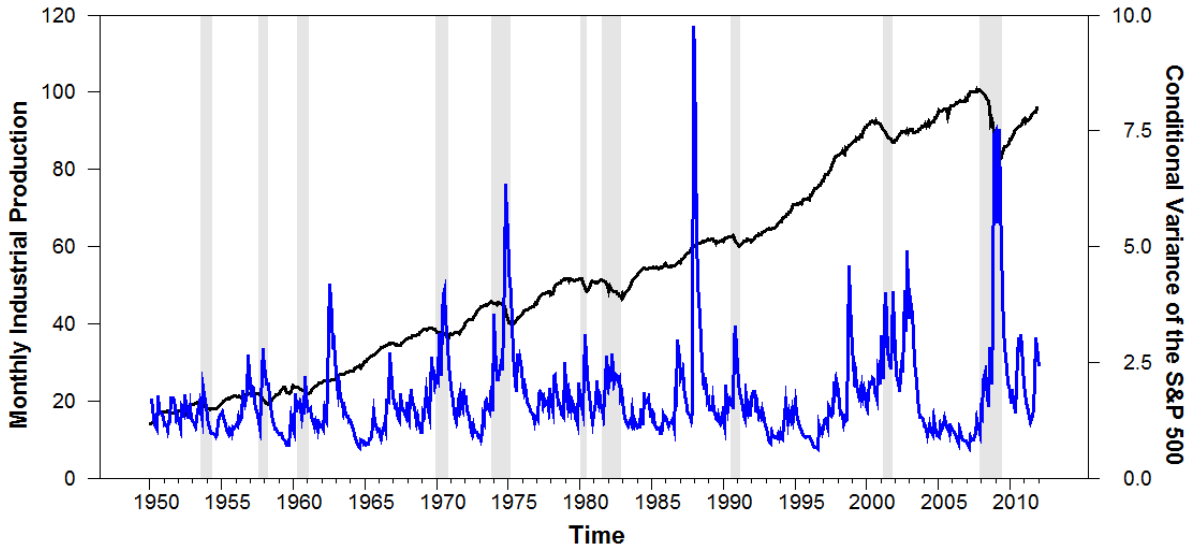
Uncertainty Measure	S&P 500 Variance	S&P 500 Variance	S&P 500 Variance	BOS Data	BOS Data	BOS Data	Uncertainty Index	Uncertainty Index	Uncertainty Index	Interest Rate Spread
Economic Activity Measure	Industrial Production	Consumer Credit	Employment	Industrial Production	Durable Goods	Consumer Credit	Industrial Production	Bank Loans	Consumer Credit	Bank Cash
α_0	0.003***	0.0031***	0.0016***	0.003***	0.008***	0.0059***	0.003***	0.001	0.0015***	0.004**
α_1	0.28***	0.61***	0.25***	0.31***	0.08	0.195*	-0.07	0.88***	0.71***	-0.007
β_0	-0.005***	-0.0026**	-0.0016***	-0.004**	-0.028	-0.0044***	-0.003***	-0.001	-0.0011	0.04*
β_1	0.35***	0.08	0.55***	0.03	-0.15	0.53***	0.45***	-0.26	-0.09	0.62***
γ [1]	5889	3097	606899	38.6	14.6	2620	13.04	19.35	10.38	8.17
c [2]	0.00225	0.0022	0.0018	0.736	0.8	0.515	115	156	152	3.96

Note: The table reports estimates for each parameter in the LSTAR model.
* Denotes statistical significance at the 90% level.
** Denotes statistical significance at the 95% level.
*** Denotes statistical significance at the 99% level.

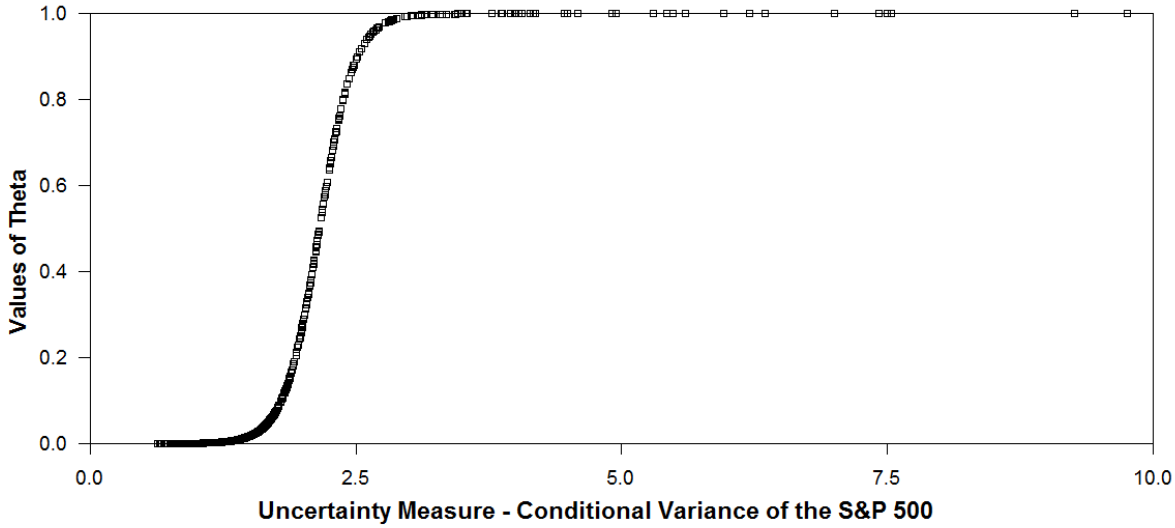
[1]The parameters are undefined when $\gamma = 0$. Therefore, significance levels for the null hypothesis $\gamma = 0$ are not reported.
[2]Also significance levels for c = 0 are not reported since our uncertainty variables are always positive.

Figure 4.1. Uncertainty and Industrial Production

Panel A: Conditional variance of the S&P 500 along with monthly U.S. industrial production



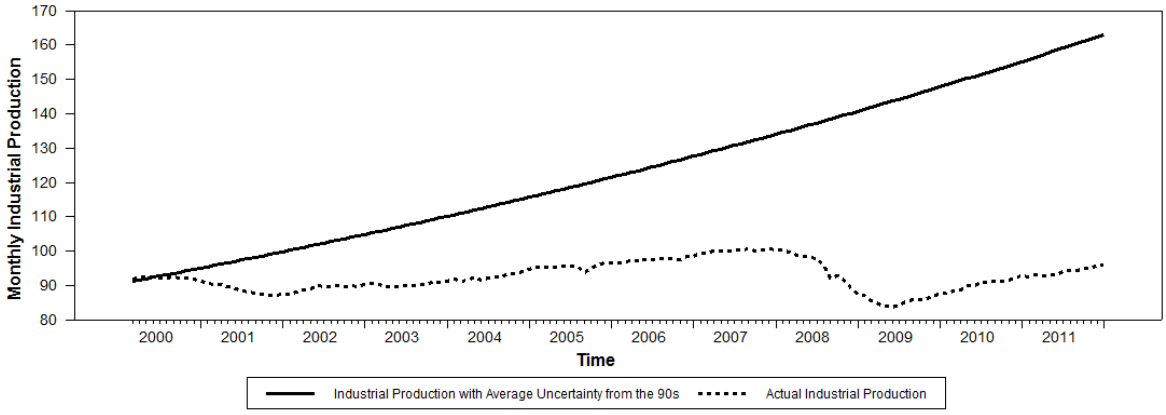
Panel B: Values of theta in the LSTAR model



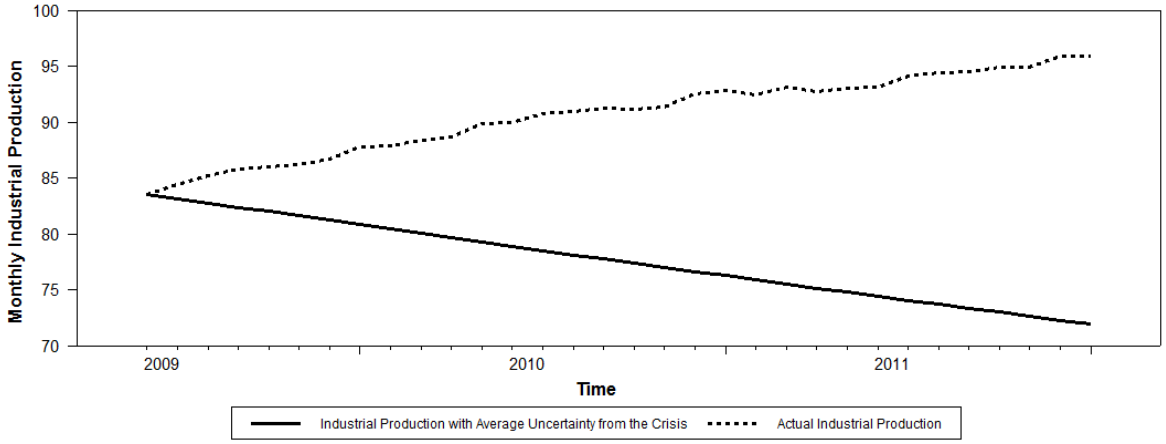
Note: Figure 4.1 shows the conditional variance estimated by an EGARCH(1,1) model normalized by dividing by the standard deviation of the series. Panel B shows values of theta in the LSTAR model where $\theta = [1 + \exp(-6.146(h_t - 2.155))]^{-1}$.

Figure 4.2. Historical Decompositions and Permanent Uncertainty Shocks

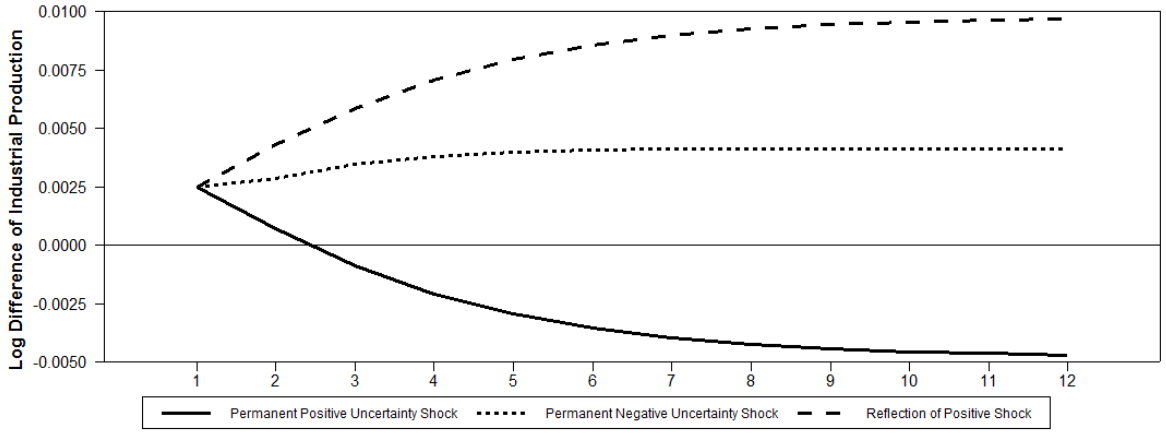
Panel A: Decomposition if uncertainty equals its average value during the 1990s



Panel B: Decomposition if uncertainty equals its average value during the financial crisis



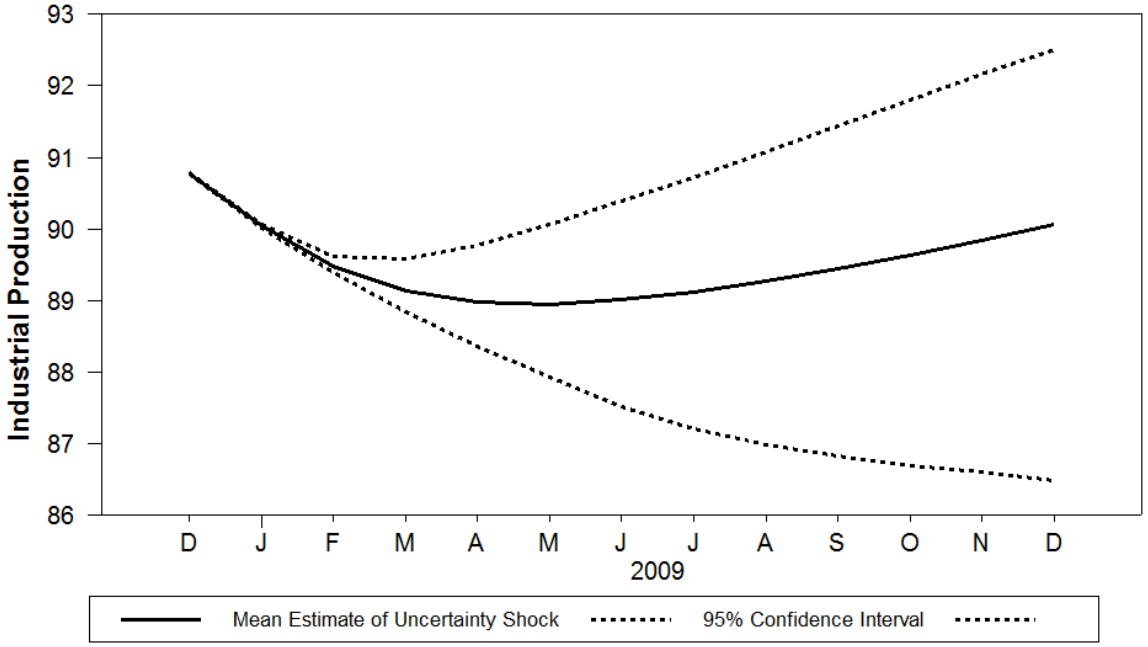
Panel C: Effects of permanent shocks to uncertainty



Note: Figure 4.2 Panel C shows the asymmetric effects of a permanent positive and a permanent negative uncertainty shock. The reflection of the positive shock shows that positive shocks have greater effects than negative shocks.

Figure 4.3. Impulse Responses to a Temporary Positive Uncertainty Shock

Panel A: Impulse response to a positive one-standard-deviation uncertainty shock occurring in 2008:12



Panel B: Impulse response to a 2008:12 uncertainty shock occurring in 2008:1

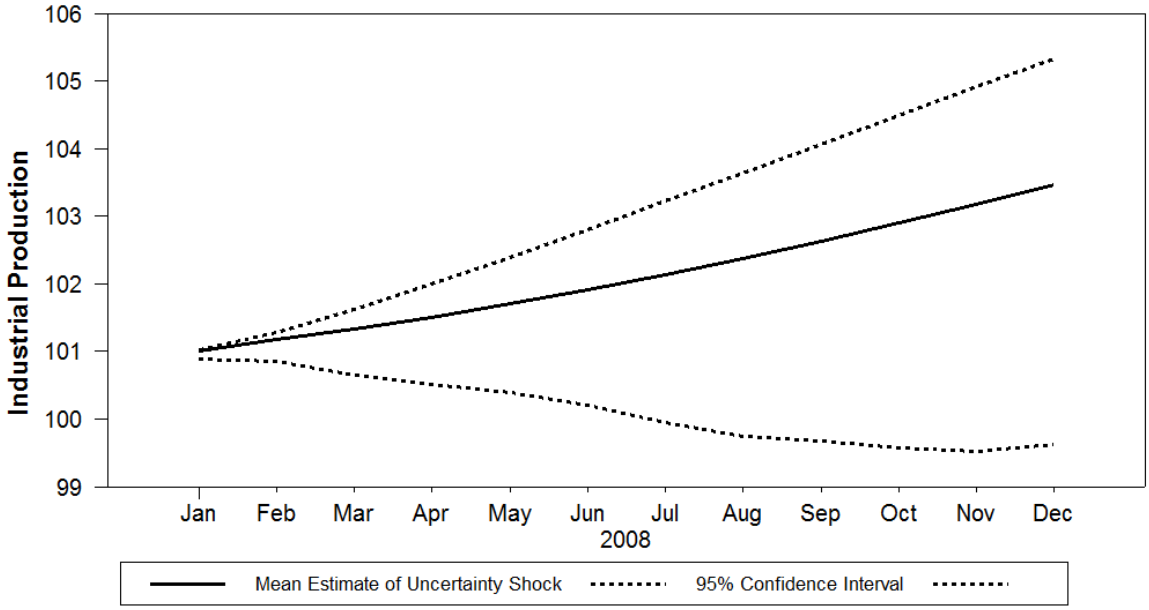
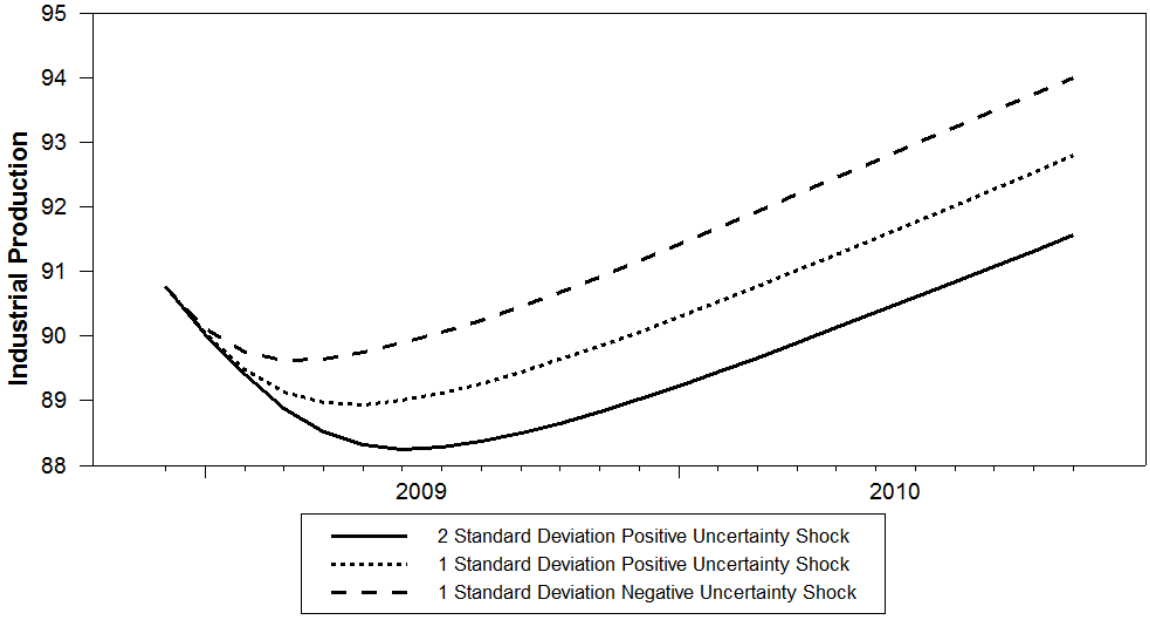
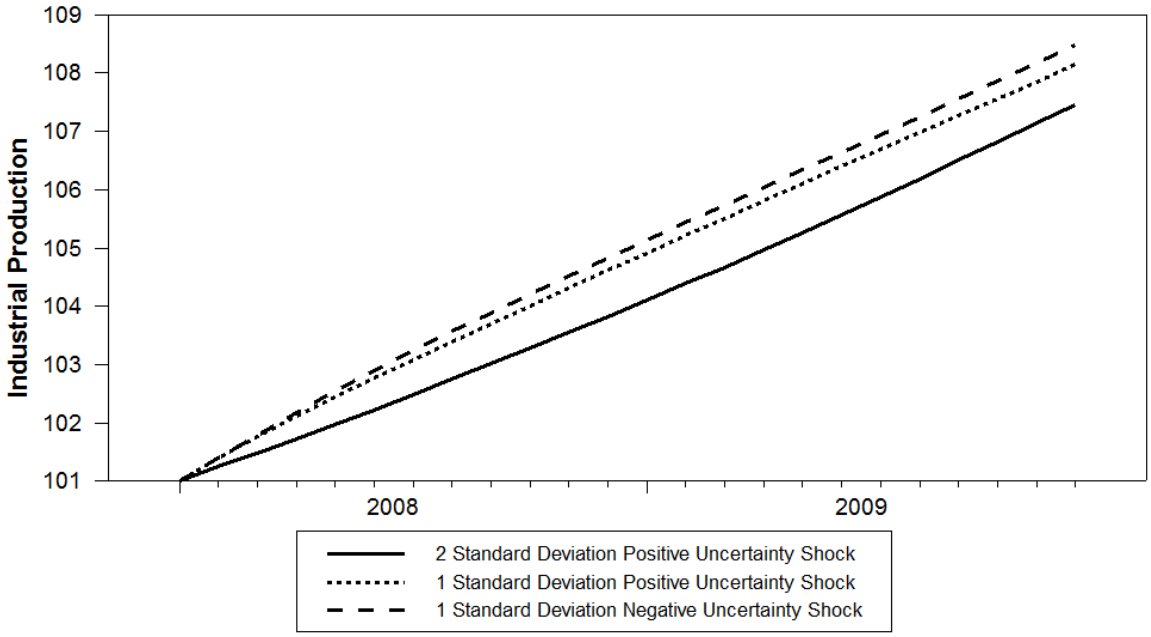


Figure 4.4. The Asymmetric Effects of Temporary Uncertainty Shocks

Panel A: Impulse responses to uncertainty shocks during the financial crisis (2008:12)

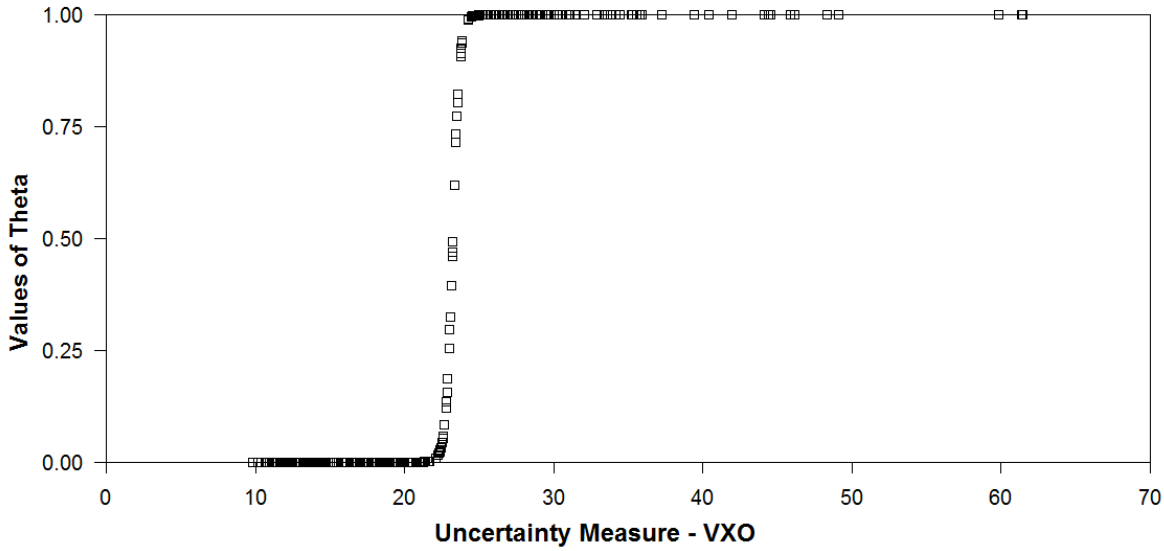


Panel B: Impulse responses to uncertainty shocks before the financial crisis (2008:1)



Note: Figure 4.4 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.

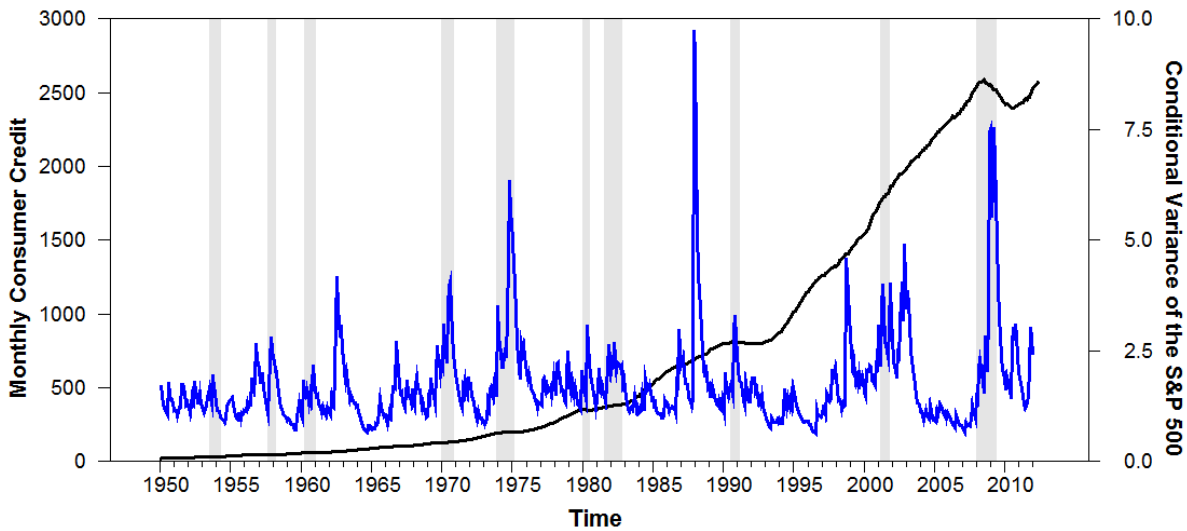
Figure 4.5. Values of Theta in the Nonlinear VAR Model



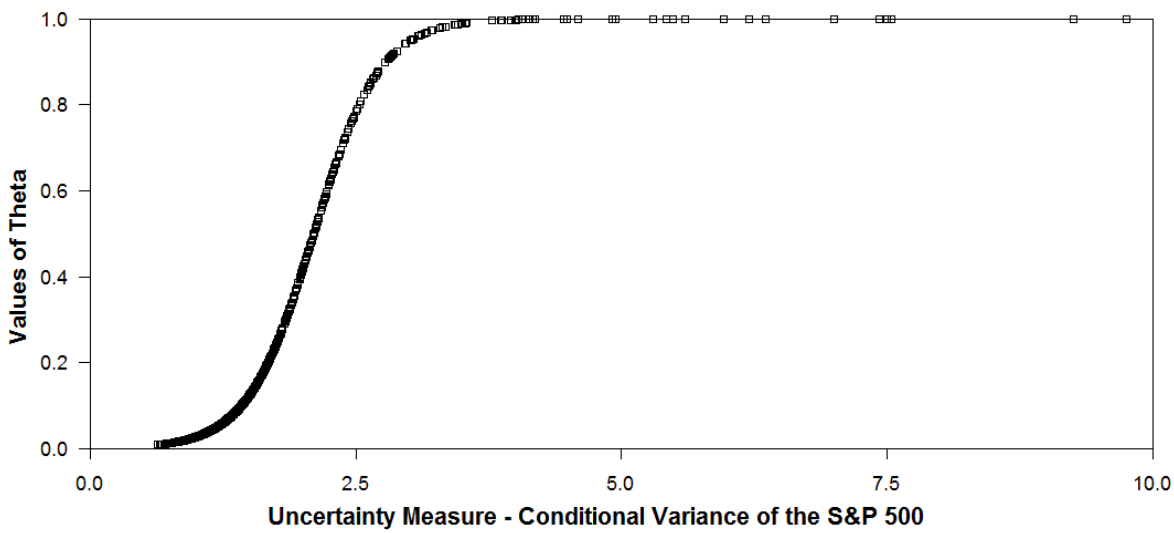
Note: The uncertainty measure in the nonlinear VAR is the implied volatility based on the Chicago Board of Options Exchange VXO index. The value of theta in the LSTAR model is defined as $\theta = [1 + \exp(-4.36(vxo_{t-1} - 23.23))]^{-1}$.

Figure 4.6. Uncertainty and Consumer Credit

Panel A: Conditional variance of the S&P 500 and monthly U.S. consumer credit



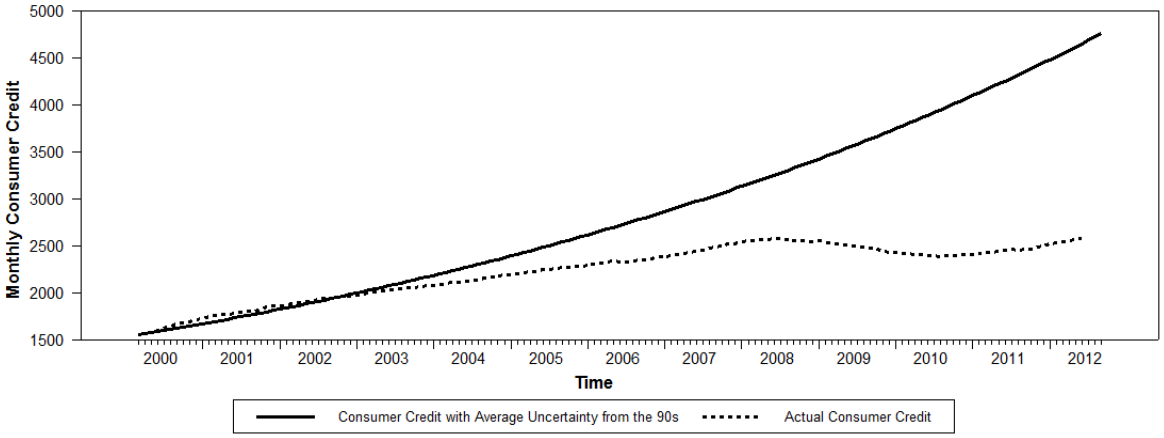
Panel B: Values of theta in the LSTAR model



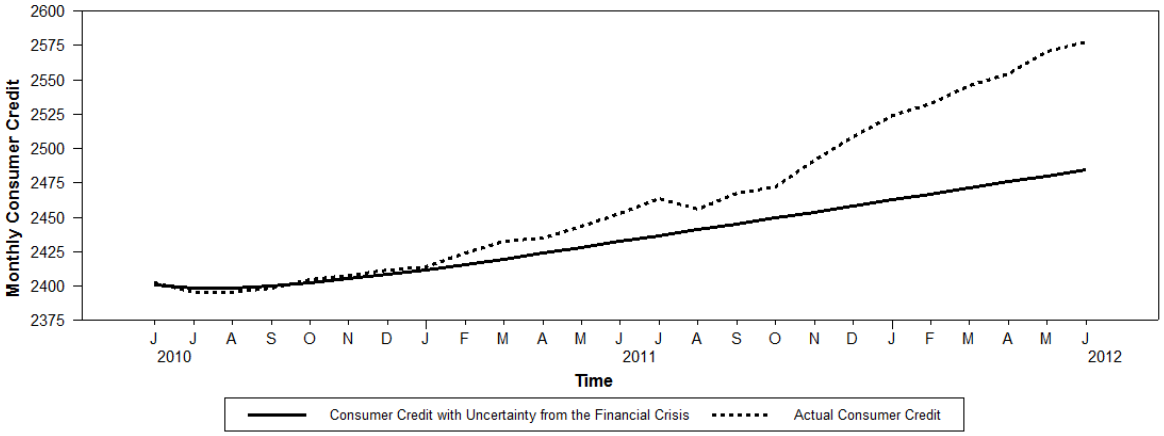
Note: Figure 4.6 shows the conditional variance estimated by an EGARCH(1,1) model normalized by dividing by the standard deviation of the series. Panel B shows values of theta in the LSTAR model where $\theta = [1 + \exp(-3.23(h_t - 2.103))]^{-1}$.

Figure 4.7. Historical Decompositions and Permanent Uncertainty Shocks

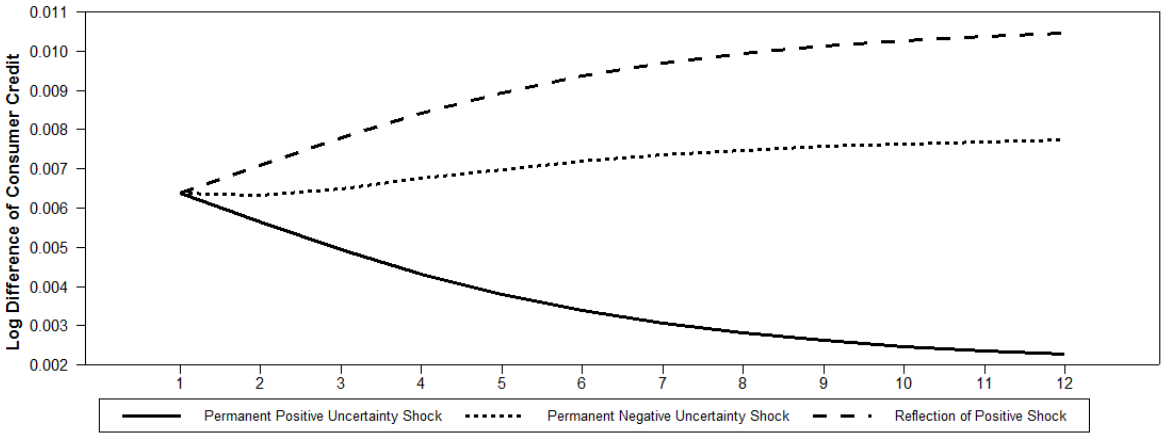
Panel A: Decomposition if uncertainty equals its average value during the 1990s



Panel B: Decomposition if uncertainty equals its average value during the financial crisis



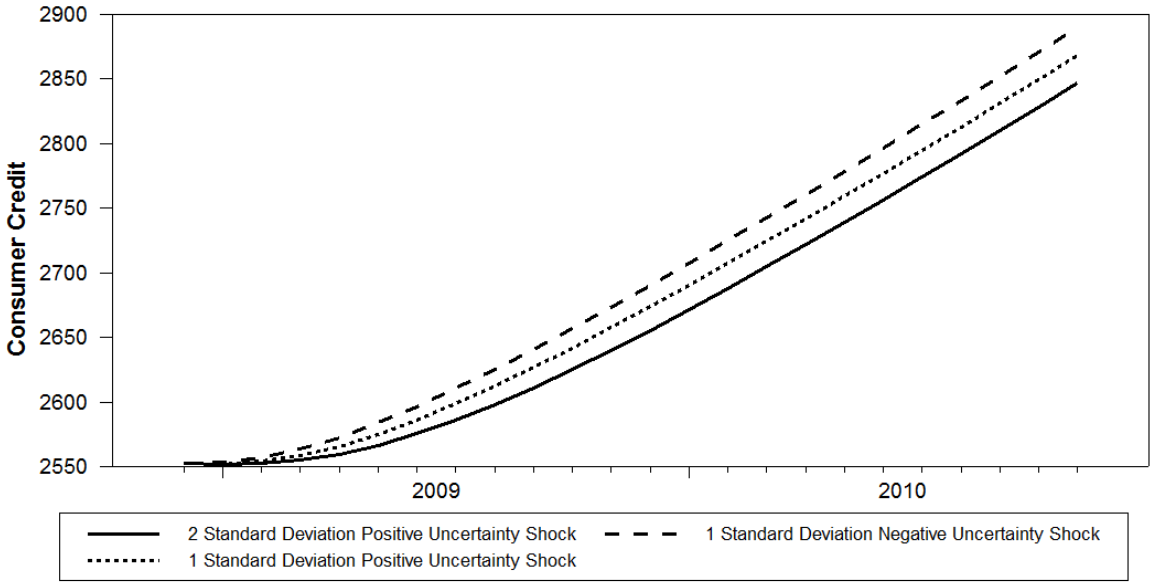
Panel C: Effects of permanent shocks to uncertainty



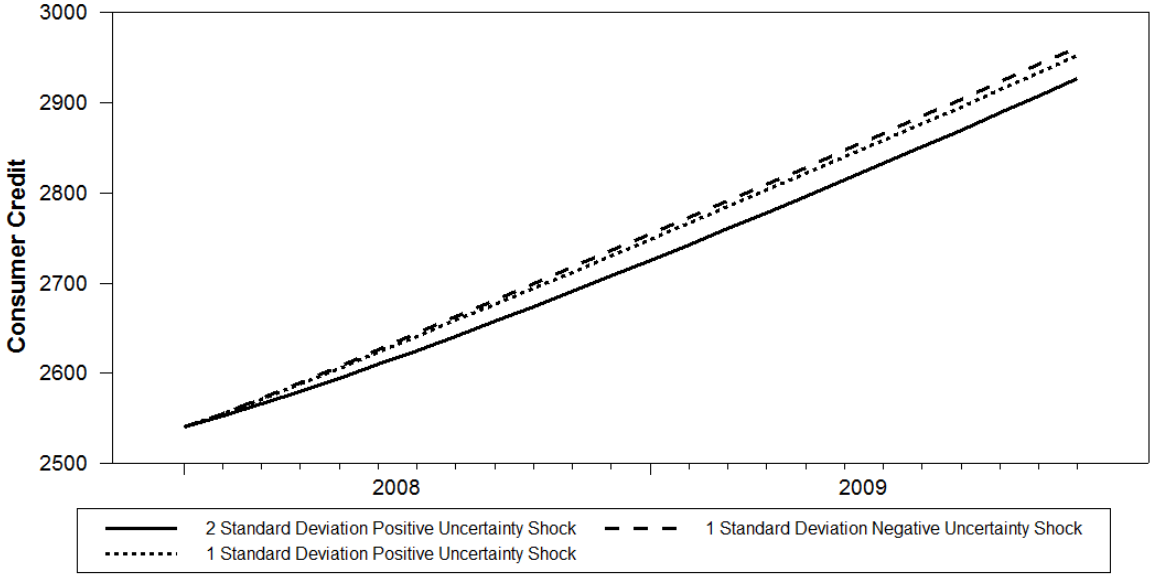
Note: Panel C shows the asymmetric effects of a permanent positive and negative uncertainty shock. The reflection of the positive shock shows that positive shocks have greater effects than negative shocks.

Figure 4.8. The Asymmetric Effects of Temporary Uncertainty Shocks

Panel A: Impulse responses to uncertainty shocks during the financial crisis (2008:12)



Panel B: Impulse responses to uncertainty shocks before the financial crisis (2008:1)



Note: Figure 4.8 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.

CHAPTER 5

CONCLUSION

In conclusion, my dissertation looks at many different measures of macroeconomic uncertainty and discovers a few empirical facts about macroeconomic uncertainty. First, macroeconomic uncertainty is countercyclical meaning the correlation between uncertainty and output is negative. However, the correlation between uncertainty and inflation appears to have changed from negative to positive in the last twenty years. Second, U.S. uncertainty appears to be a potential driver of global business cycles, and the effects of a U.S. uncertainty shock are similar to a demand shock. Finally, the effects of an increase in uncertainty appear to have much greater effects than a decrease in uncertainty and the timing of the uncertainty shock larger determines its effects.

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