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Uncertainty and Unemployment: The Effects of Aggregate and Sectoral Channels

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Uncertainty and Unemployment: The Effects of Aggregate and Sectoral Channels

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Abstract

We study the role of uncertainty shocks in explaining unemployment dynamics, separating out the role of aggregate and sectoral channels. Using S&P500 data from the first quarter of 1957 to third quarter of 2014, we construct separate indices to measure aggregate and sectoral uncertainty and compare their effects on the unemployment rate in a standard macroeconomic vector autoregressive (VAR) model. We find that aggregate uncertainty leads to an immediate increase in unemployment, with the impact dissipating within a year. In contrast, sectoral uncertainty has a long-lived impact on unemployment, with the peak impact occurring after two years. The results are consistent with a view that the impact of aggregate uncertainty occurs through a "wait-and-see" mechanism while increased sectoral uncertainty raises unemployment by requiring greater reallocation across sectors.

JEL Classification Numbers: E24, E32, E44, J64

Keywords: aggregate uncertainty; sectoral uncertainty; unemployment; stock market; Great Recession

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I. INTRODUCTION

This paper examines the effect of uncertainty shocks on the U.S. labor market. We analyze U.S. stock market data to determine how two types of uncertainty shocks (aggregate and sectoral) affect the U.S. unemployment rate. By estimating a structural vector autoregressive (VAR) model of the U.S. economy from the first quarter of 1957 (1957Q1) to the third quarter of 2014 (2014Q3), we find that the two shocks have different effects. Aggregate uncertainty shocks—as measured by the realized volatility of aggregate stock returns—lead to an immediate but short-lived increase in the unemployment rate. In contrast, sectoral uncertainty shocks—as measured by the cross-industry volatility of stock returns—have more significant, persistent effects on the unemployment rate and are especially important in explaining the long-term unemployment rate (longer than 26 weeks). The substantial increase in the long-term unemployment rate since 2007 can be attributed largely to sectoral, not aggregate, uncertainty.

The sharp rise in the U.S. unemployment rate since 2007 has triggered a debate on the driving factors of high unemployment rates. In 2014Q3, the long-term unemployment rate remained above 2 percent, significantly higher than the 0.7 percent rate recorded in 2007. Among possible factors, economic uncertainty has been blamed for the sluggish recovery in the U.S. labor market. Bloom's (2009) seminal research shows that, in the presence of uncertainty, a wait-and-see mechanism can be a driver of the U.S. business cycle. Uncertainty is inherently unobservable, so researchers focus on constructing a measure of time-varying uncertainty from various sources of data. Our first contribution is to construct two separate indices that capture aggregate and sectoral uncertainty from a common source: the volatility of the U.S. stock market.[2]

Uncertainty shocks have a clear theoretical effect on the evolution of the unemployment rate with the presence of labor adjustment costs, as Bloom (2009) suggests. According to this mechanism, the option value of waiting increases when uncertainty is high, causing firms to be more cautious in their hiring and firing decisions. To test this theoretical prediction, Bloom (2009) constructs an uncertainty index based on the monthly realized and the implied volatility of the S&P500. While modeling both macro-and micro-level uncertainty, Bloom (2009) assumes that the same stochastic process drives both, because a measure of aggregate uncertainty is well correlated with other measures of cross-sectional uncertainty, such as the dispersion of firms' profit growth, stock returns, and industry-level productivity growth.

Despite the high correlation between the indices of the two types of uncertainty, their effects on labor markets might differ because labor is distinct from other factors of production. Workers accumulate industry-specific human capital over time, making the inter-industry reallocation of

[2] While analysis of the effects of stock market volatility on business cycle has a long history (e.g., Schwert 1989, Hamilton and Lin 1996), separating the effects of aggregate and cross-industry stock market volatility has not been done before to our knowledge.

labor more costly than intra-industry reallocation. When such frictions are large, sectoral uncertainty might have a stronger effect on the labor market than aggregate uncertainty. However, the literature does not distinguish between the effects of these types of uncertainty.

We fill this gap by comparing the effects of sectoral uncertainty and aggregate uncertainty shocks on the unemployment rate. We rely on earlier work to justify our two uncertainty indices which capture different types of uncertainty. Loungani and others (1990) and Brainard and Cutler (1993) use the cross-sectional volatility of the U.S. stock market as a proxy for sectoral shocks to study the effect on unemployment. They reason that increases in unemployment follow periods of greater cross-industry dispersion in stock returns because greater sectoral dispersion motivates the reallocation of labor across industries (Black 1995), which is more costly than reallocation within the same industry. Therefore, if the sectoral uncertainty index captures a need for inter-industry labor reallocation on top of economy-wide uncertainty, sectoral uncertainty shocks are expected to have more persistent effects than aggregate uncertainty shocks on the unemployment rate.

We provide three new empirical findings. First, the unemployment rate has sharply different dynamic responses to aggregate uncertainty and sectoral uncertainty shocks. While aggregate uncertainty shocks have short-lived effects on the unemployment rate (peaking in two quarters and becoming statistically insignificant after four quarters), sectoral uncertainty shocks have more persistent effects (peaking in two years and becoming statistically insignificant after three years).

Second, the share of unemployment fluctuations attributed to sectoral uncertainty shocks increases significantly when moving from short-term to long-term unemployment. Aggregate uncertainty shocks, however, show an opposite pattern of monotonic decreases in moving from long- to short-term unemployment. These results suggest that aggregate and sectoral uncertainty shocks are correlated with unemployment of different durations.

Finally, the sectoral uncertainty during the Great Recession helps explain why long-term unemployment has been such a prominent feature of its aftermath, but aggregate uncertainty shocks have played a minor role. This finding can explain the recent findings of Born and others (2014) and Caldara and others (2014) that uncertainty shocks played a minor role in employment fluctuations during the Great Recession when considering only aggregate uncertainty shocks.

The remainder of this paper is organized as follows. Section II provides an economic explanation of the distinct mechanisms of two uncertainty shocks and presents two indices of uncertainty. In section III, we discuss our VAR model in detail and summarize our empirical results, including robustness checks. Section IV presents our conclusions.

II. Measuring Uncertainty: Aggregate vs. Sectoral

Measuring uncertainty of any kind is not a straightforward exercise because of the unobservable nature of uncertainty. However, researchers have attempted to measure time-varying uncertainty from various sources: aggregate stock market volatility (Bloom 2009), forecast errors constructed from firm-survey data (Bachmann and others 2013), the frequency of newspaper references to policy uncertainty (Baker and others 2013), direct consumer survey data (Leduc and Liu 2012), and unpredictable components of economic indicators (Jurado and others 2013). Following the definition developed by Bloom and others (2012), we impose a structural interpretation of our uncertainty indices.

Bloom and others (2012) define uncertainty as an increase in the variance of underlying shocks to the economy. For example, assume that a firm indexed by j produces output in period t according to the following production function:

$$y_{j,t} = A_t z_{j,t} f(k_{j,t} l_{j,t}),$$

where $k_{j,t}$ and $l_{j,t}$ represent idiosyncratic capital and labor employed by the firm, respectively. Each firm's productivity can be understood as the product of two separate processes: an aggregate component, A_t, and an idiosyncratic component, $z_{j,t}$. The aggregate and idiosyncratic components further follow an autoregressive process:

$$\log(A_t) = \rho^A \log(A_{t-1}) + \sigma_{t-1}^A \varepsilon_t,$$

$$\log(z_{j,t}) = \rho^Z \log(z_{j,t-1}) + \sigma_{t-1}^Z \varepsilon_{j,t},$$

where σ_t^A and σ_t^Z stand for time-varying aggregate and idiosyncratic uncertainty.[3] Aggregate uncertainty implies that all firms are affected by more volatile shocks, while idiosyncratic uncertainty entails large productivity dispersion across firms. Although most earlier researchers studied only one type of uncertainty shock because of the high correlation between them, we evaluate the effect of both types of uncertainty shocks in a common framework.

For this purpose, we construct two uncertainty indices to capture different dimensions of the U.S. stock market's volatility: aggregate vs. cross-industry volatility. Uncertainty is not fully exogenous to economic conditions, so existing measures of uncertainty typically are purged of the impacts of other variables. For example, Bloom (2009) controls for the level of U.S. stock market in his VAR. The advantage of our method is that we can purge two uncertainty indices using the same variable (U.S. stock returns) and focus only on the volatility component of the U.S. stock market. Purging for other measures of uncertainty from different data sources is not straightforward.

In the research most similar to the present work, Bijapur (2014) studies the potentially different roles of aggregate and firm-level uncertainty shocks in the U.S. business cycle. Instead of firm-

[3] Bloom (2009) imposes $\sigma_t^A = \sigma_t^B = \sigma_t$, based on the high correlation between macro- and micro-level volatility.

level stock market volatility, however, we use industry-level stock volatility as a proxy for sectoral uncertainty. Whereas Bijapur (2014) describes a horse race between aggregate and firm-level uncertainty shocks to explain the U.S. business cycle, we are particularly interested in the effect of uncertainty shocks on the labor market based on the theoretical hypothesis that inter-industry labor reallocation is more costly than intra-industry reallocation.

A. The Effect of Uncertainty Shocks on Unemployment: Different Explanations

The wait-and-see mechanism is one of the most well-known means through which uncertainty shocks affect a real economy. As greater uncertainty increases the real option value of waiting, firms scale back their investment and hiring plans (Bernanke 1983, Dixit and Pindyck 1994, Abel and Eberly 1996, Caballero and Engel 1999) in the presence of partial irreversibility. In a recent contribution, Bloom (2009) quantifies this mechanism by showing a "sharp drop and rapid rebound" in the response pattern of production and employment to uncertainty shocks. Our aggregate uncertainty index is similar to the one in Bloom's (2009) exercise, so we can expect a short-lived effect on the unemployment rate.

Lilien (1982) shows how sectoral shocks affect a labor market by constructing a cross-industry employment dispersion index as a proxy for the intersectoral flow of labor caused by sectoral shocks. Inter-industry labor reallocation is more costly than intra-industry reallocation (Shin 1997, Phelan and Trejos 2000, Lee and Wolpin 2006), so unemployment rises after an increase in the intersectoral labor flow. In response to Abraham and Katz's (1986) critique that employment dispersion might simply reflect non-neutral effects of the business cycle across industries, Loungani and others (1990) and Brainard and Cutler (1993) use cross-industry stock market volatility to measure sectoral dispersion.

The industry stock price represents the present value of expected profits over time; consequently, persistent shocks will have a significant impact on expected future profits and lead to larger changes in industries' stock prices than temporal shocks. Therefore, the uncertainty index constructed from industries' stock prices assigns greater weight to permanent structural changes than to temporary shocks so that it is less likely to reflect aggregate demand disturbances than a measure of aggregate uncertainty.

B. Construction of the Uncertainty Indices from the U.S. Stock Market

The aggregate uncertainty index equals the realized volatility of the S&P500 index returns. The design of this uncertainty index is similar to that of realized volatility in Bloom (2009).[4] For each quarter t, we construct the aggregate uncertainty index as follows:

[4] There is a minor difference: while Bloom (2009) constructs his uncertainty measure based on monthly frequency, we do not aggregate the monthly uncertainty index to the quarterly frequency because time aggregation mechanically reduces the volatility of the uncertainty index, as pointed out by Fernandez-Villaverde and others (2011).

$$RV_t = \left[\sum_{s=1}^{S} \frac{252}{S} \left(R_{s,t} - \overline{R}_t \right)^2 \right]^{1/2},$$

where S is the number of trading days in each quarter, $R_{s,t}$ is the market returns on day s, and $\overline{R}_t$ is the average of market returns during each quarter. In other words, our aggregate uncertainty index is the annualized standard deviation of daily aggregate stock returns over a quarter.

We construct the sectoral uncertainty index using industry-level quarterly returns to capture the long-term swing of stock prices. To address the potential problem of different sensitivity of industry returns to market returns (i.e., different betas),[5] we first regress industry returns $R_{i,t}$ on market returns: $R_t : R_{i,t} = \alpha_i + \beta_i R_t + \varepsilon_{i,t}$. We then calculate the dispersion of excess returns: $\eta_{i,t} = \hat{\alpha}_i + \hat{\varepsilon}_{i,t}$. After controlling for different betas, the sectoral uncertainty index is defined as:

$$CSV_t = \left[\sum_{i=1}^{n} W_i \left(\eta_{i,t} - \overline{\eta}_t \right)^2 \right]^{1/2},$$

where $\overline{\eta}_t$ is the average excess returns in period t and W_i is a weight based on the industry's share in total employment.[6]

Figure 1 shows the behavior of the two measures of uncertainty from 1957Q1 to 2014Q3 based on a quarterly frequency. To ease comparison, we normalize both indices so that they have the same mean and variance.[7] Figure 2 presents a histogram of the numerical values for each index. As in Bloom (2009) and Bloom and others (2012), both measures of uncertainty are strongly countercyclical and increase sharply during the Great Recession. Although two measures are moderately correlated with a correlation coefficient of 0.54, they do not always move together, implying that there is the possibility of testing whether each type of uncertainty has a different role in shaping labor market dynamics. The persistence of both indices, measured by their

[5] Brainard and Cutler (1993) note that some industry stock returns might be more cyclically sensitive, so aggregate shocks can increase the dispersion of returns. Brainard and Cutler (1993) introduce a modified measure which attempts to eliminate these cyclical effects by first regressing industry returns on market returns. The dispersion index then constructs the excess returns, or the residuals from these regressions. Our main results do not depend on whether we use returns, as in Loungani and others (1990), or excess returns, as in Brainard and Cutler (1993).

[6] See the Appendix for details.

[7] Although both indices have the same first two moments of construction, they have the different third and fourth moments: Skewness and kurtosis are 3.30 and 20.27 for the aggregate uncertainty index and 1.71 and 7.04 for the sectoral uncertainty index, implying that the aggregate uncertainty index contains more extreme values.

AR(1) coefficients, is similar (aggregate uncertainty index: 0.58; sectoral uncertainty index: 0.53).[8]

Figure 3 shows the main subject of interest—the history of the overall unemployment rate during the sample period—along with the long-term unemployment rate. The unprecedented increase in the long-term unemployment rate during the Great Recession stands out, so we give extra effort to explain its contributing factors.

III. Structural VARs

In this section, we present the results from the structural VARs estimated using quarterly U.S. data from 1957Q1 to 2014Q3. The baseline model has seven variables, including the two uncertainty indices and the unemployment rate. Similar to the work of Chen and others (forthcoming), we include the following standard macroeconomic variables: quarterly real GDP growth rate, quarterly returns on the S&P500 Index, inflation rate, and the federal funds rate. The real GDP captures the stage of the business cycle, while controlling for the quarterly returns on the S&P500 Index rules out the possibility that the uncertainty index explains unemployment because of the negative relationship between stock volatility and its returns (Campbell and Hentschel 1992). Following Bernanke and Blinder (1992), we include the federal funds rate as a measure of monetary policy.

The system is identified following a standard recursive ordering procedure. The variables in the system are ordered as follows: stock market returns, two uncertainty indices, inflation, the federal funds rate, real GDP growth, and unemployment rate. This recursive ordering is based on the assumption that shocks immediately affect the stock market and then prices (inflation and interest rates) and quantities (output and unemployment rate), similar to Bloom's (2009) identification. The lag length is set at four because of the quarterly frequency of data. Thus, we write our VAR system as follows:

$AY_t = \sum_{k=1}^{4} B_k Y_{t-k} + \varepsilon_t, \qquad Y_t = \left(\Delta SP500_t,\ VOL_t,\ \pi_t,\ r_t,\ \Delta GDP_t,\ UN_t \right)'$, where ε_t is the vector of structural shocks, Δ represents the first-order log difference, and $VOL_t = \left(RV_t,\ CSV_t \right)'$. In the following section, to evaluate the marginal role of each type of uncertainty shock, we control for the aggregate uncertainty index when evaluating the role of sectoral uncertainty, and vice versa.[9] There is no clear theory to justify a zero restriction

[8] The higher persistence in the aggregate uncertainty index than the sectoral uncertainty index indicates that our main results are not simply driven by their statistical properties, without any economic implications.

[9] This identification assumption means that $Y_t = \left(\Delta SP500_t,\ RV_t,\ CSV_t,\ \pi_t,\ r_t,\ \Delta GDP_t,\ UN_t \right)'$ when we evaluate the effect of CSV_t and $Y_t = \left(\Delta SP500_t,\ CSV_t,\ RV_t,\ \pi_t,\ r_t,\ \Delta GDP_t,\ UN_t \right)'$ when we evaluate the effects of RV_t.

between two types of uncertainty, so our identification assumption is more robust to a model misspecification.

A. The Effects of Uncertainty Shocks

Figures 4 and 5 show the effects of aggregate and sectoral uncertainty shocks on macroeconomic variables, along with the associated 90 percent confidence intervals.[10] Aggregate and sectoral uncertainty shocks have similar qualitative effects on the U.S. business cycle, in line with earlier research. In particular, the effects of aggregate uncertainty shocks on the inflation, federal funds, GDP growth, and unemployment rates are consistent with Leduc and Liu's (2012) conclusion that uncertainty shocks are a negative aggregate demand shock. Despite the statistical insignificance of the response of inflation and federal funds rates, the impact of sectoral uncertainty shocks shares similar dynamics.

We pay particular attention to the response of the unemployment rate to uncertainty shocks. The unemployment rate rises after an increase in both uncertainty indices, but the dynamic patterns are quite different. On one hand, an increase of one standard deviation in the aggregate uncertainty index leads to an instant 0.06 percentage point increase in the unemployment rate, which becomes statistically insignificant after three quarters. On the other hand, an increase of one standard deviation in the sectoral uncertainty index leads to a nearly 0.2 percentage point increase in the unemployment rate, which remains statistically significant for more than three years. Sectoral uncertainty shocks seem to have more significant and persistent effects on the unemployment rate than aggregate uncertainty shocks.[11]

The forecast error variance decomposition of the unemployment rate provides further evidence of the two uncertainty indices' relative importance in explaining fluctuations in unemployment. Figure 6 shows the variance in forecast errors explained by aggregate uncertainty shocks for unemployment of different durations over 20 quarters. Changes in the aggregate uncertainty index explain only 1.5 percent of the variance in the unemployment forecast errors.[12] Figure 6 illustrates an interesting pattern: The variation in unemployment explained by the aggregate uncertainty index decreases monotonically with the duration of unemployment, suggesting that the effect of aggregate uncertainty shocks is short lived.

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[10] Standard errors are estimated using a parametric bootstrapping procedure with 500 repetitions. I do not report the response of each type of uncertainty shocks to itself because of space constraints.

[11] We also estimate our model using levels of variables with quadratic trends, instead of the variables' log of difference. The impacts of both types of uncertainty shocks on unemployment decrease somewhat but remain statistically significant.

[12] Even without controlling for the sectoral uncertainty index, the aggregate uncertainty index only explains 2 percent.

Figure 7, however, shows an opposite pattern. Changes in the sectoral uncertainty index explain approximately 15 percent of the variance of unemployment forecast errors. Additionally, the proportion of the variation in unemployment explained by sectoral uncertainty shocks increases monotonically with the duration of unemployment. Sectoral uncertainty shocks account for virtually none of the variation in the short-term unemployment rate. However, when unemployment lasts longer than 26 weeks, sectoral uncertainty shocks account for more than 30 percent of the variance in the forecast error, implying that this type of uncertainty shock plays an important role in explaining the sharp increase in the long-term unemployment rate during the Great Recession.

We further investigate the different effects of the two uncertainty indices by illustrating the dynamic response of the long-term unemployment rates. The long-term unemployment rate (Figure 8) shows similar pattern as the overall unemployment rate (Figures 4 and 5).

B. Contribution of Uncertainty Shocks to Long-Term Unemployment during the Great Recession

We use the estimated VAR to examine fluctuations in long-term unemployment during the Great Recession. Long-term unemployment accounted for 18 percent of total unemployment in the fourth quarter of 2007 and remained high, at 32 percent, in the 2014Q3, long after the official end of the Great Recession.

Figure 9 shows a plot of the long-term unemployment rate since the beginning of 2008 and the contribution of the two types of uncertainty. The base period chosen is the fourth quarter of 2007 (2007Q4), declared as the official start of the recession by the U.S. National Bureau of Economic Research. The forecast horizon extends to the third quarter of 2014, for a total of 27 quarters. The line labeled “baseline projection” plots the conditional expectation for the long-term unemployment rate over these 27 quarters as of 2007Q4. The contribution of each type of uncertainty shocks is measured by the VAR forecast for the long-term unemployment rate if the orthogonalized aggregate and sectoral uncertainty shocks from 2008Q1 to 2014Q3 had been known at the end of 2007. While sectoral uncertainty shocks emerge as quite important in explaining the realized long-term unemployment rate’s deviation from the baseline forecast, aggregate uncertainty shocks contribute little.[13]

C. Robustness Checks

To support our main claim that sectoral uncertainty shocks have more significant and persistent effects on unemployment as suggested by the reallocation mechanism, we perform a battery of robustness checks. To highlight the subject of interest, we report results only for the unemployment rate.

[13] To obtain a conservative result, we place the aggregate uncertainty index before the sectoral uncertainty index in the VAR system.

First, Beetsma and Giuliodori (2012) and Choi (2013) find that the effect of uncertainty shocks on real economy has decreased substantially over time. As these researchers' proxies of uncertainty are similar to our aggregate uncertainty index, it is necessary to check whether the effect of sectoral uncertainty shocks on the unemployment rate falls over time. We re-estimate our VAR model with data from first quarter of 1984 (1984Q1) to 2014Q3. The results reported in the left panel of Figure 10a confirm the finding of Beetsma and Giuliodori (2012) and Choi (2013) because the effect of aggregate uncertainty shocks declines substantially. However, the effect of sectoral uncertainty shocks remains strong, as shown in the right panel of Figure 10a. We further drop the Great Recession period and re-estimate our VAR model with data from 1984Q1 to 2007Q4 to rule out the role of the Great Recession. Again, Figure 10b still shows a persistent effect of sectoral uncertainty shocks on the unemployment rate.

Second, although we employ a standard VAR model based on economic theory, misspecification issues remain. In particular, the seven variables in the baseline model imposes a heavy load on the estimation of parameters. Therefore, we adapt a parsimonious VAR model which includes only four variables: real GDP growth, both uncertainty indices, and the unemployment rate. Figure 11 shows that qualitative results reported in Figures 5 and 6 hold true. The response of unemployment to real GDP shocks is consistent with estimates of Okun's Law reported by Blanchard (1989) and Ball, Leigh and Loungani (2013). However, even after controlling for real GDP growth, sectoral uncertainty shocks have a strong and persistent effect on the unemployment rate.

Third, to check the robustness of our results to the ordering of the VAR, we reverse the ordering of our baseline VAR model. By placing our uncertainty indices at the end of the Cholesky ordering, we obtain more conservative estimates for the effect of uncertainty shocks. As seen in Figure 12, aggregate uncertainty shocks have a statistically significant effect on the unemployment rate only in the short term, whereas sectoral uncertainty shocks have a significant effect for up to three years.

Finally, we use four lags in our baseline estimation based on the nature of quarterly variables and the suggestion from Akaike information criterion. But we also re-estimate our baseline model with eight lags. Again, Figure 13 shows that the qualitative results remain similar.

IV. CONCLUSION

This paper contributes to the growing literature on measuring uncertainty and quantifying its macroeconomic effects. We provide empirical evidence that aggregate and sectoral uncertainty shocks have different effects on U.S. unemployment. Aggregate uncertainty has short-lived impacts whereas sectoral uncertainty has more persistent impacts. The results from forecast error variance decomposition of unemployment at different durations suggest that sectoral uncertainty is particularly relevant for understanding the dynamics of long-term unemployment.

Economic theory suggests that uncertainty can result in higher unemployment through various channels. By exploiting different dimensions of uncertainty (aggregate vs. sectoral), we show that the effects of each of uncertainty shocks on U.S. unemployment are consistent with the predictions made by different channels (wait-and-see vs. reallocation). To strengthen the independent channels through which aggregate and sectoral uncertainty affect unemployment, developing an integrated model that jointly evaluates both types of uncertainty will be a fruitful direction for future research.

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Figure 1. Uncertainty Index

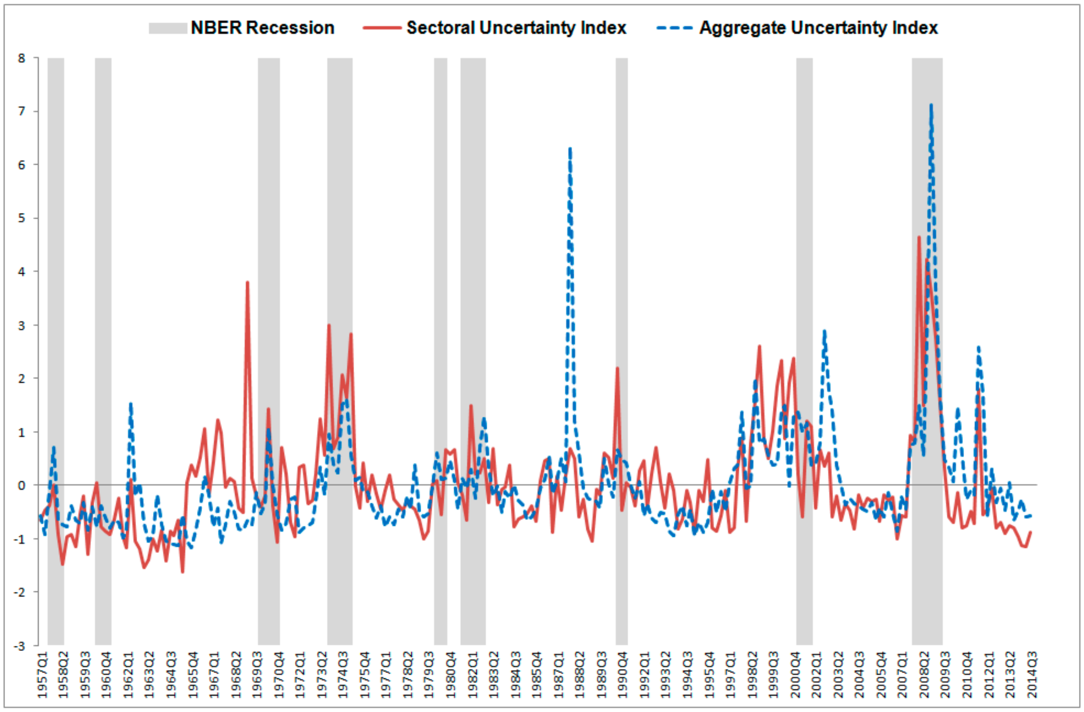


Figure 2. Distribution of Aggregate and Sectoral Uncertainty Indices

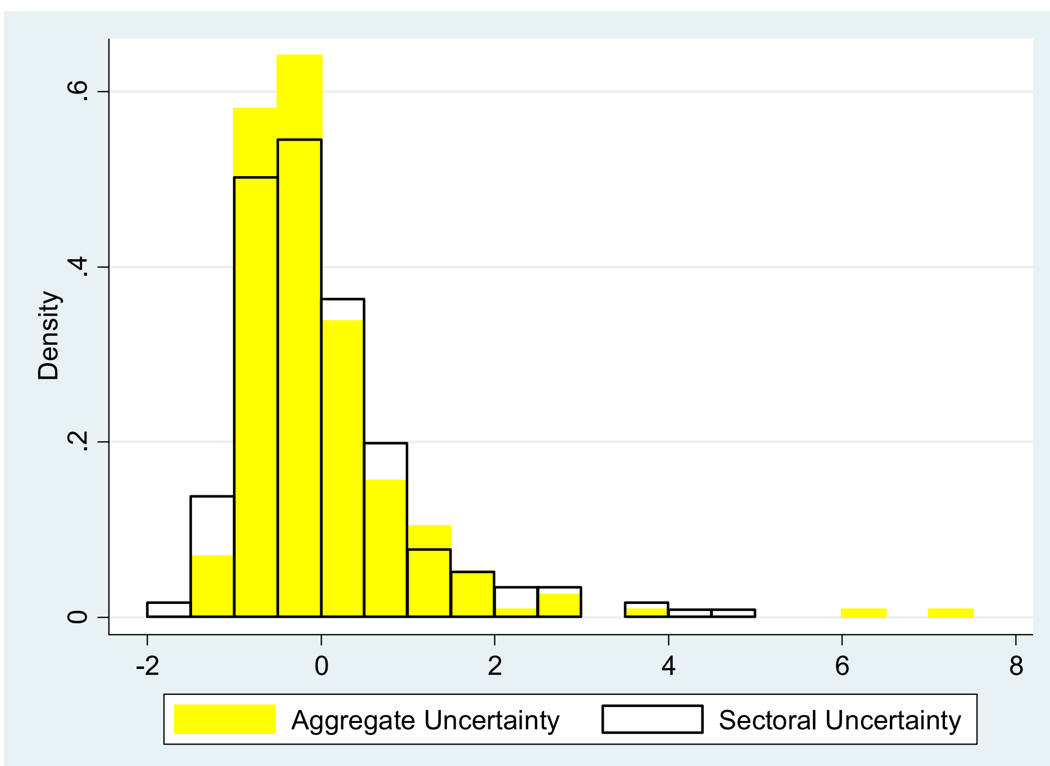


Figure 3. Unemployment Rate (Percent)

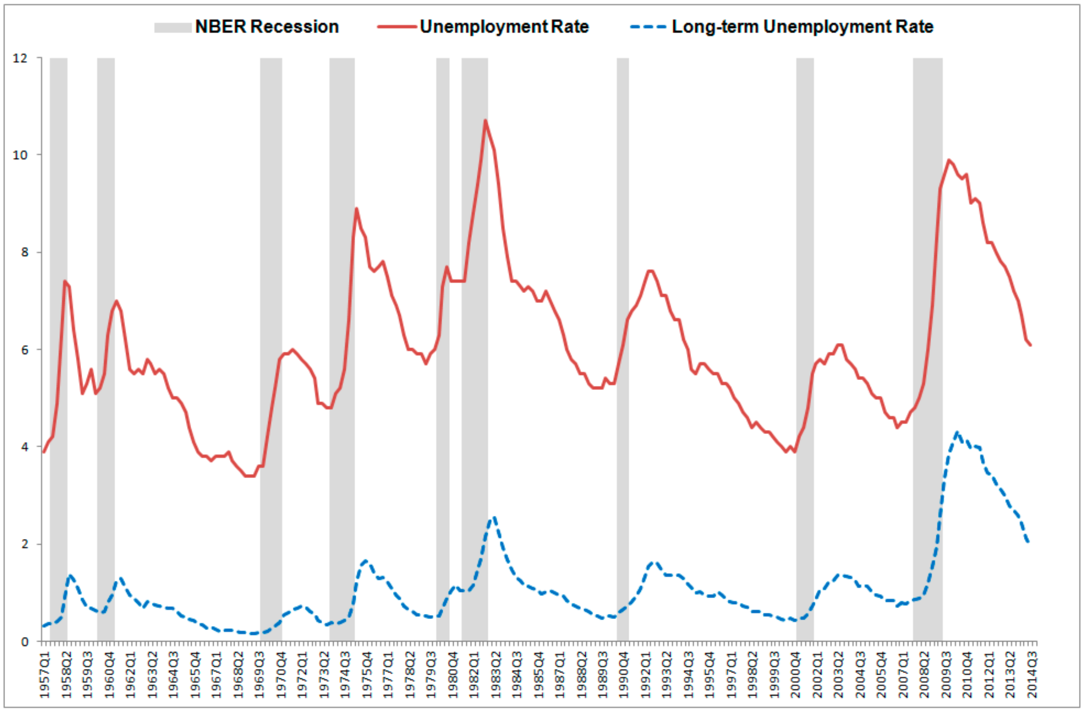


Figure 4. Response to Aggregate Uncertainty Shocks (7 Variable VAR)

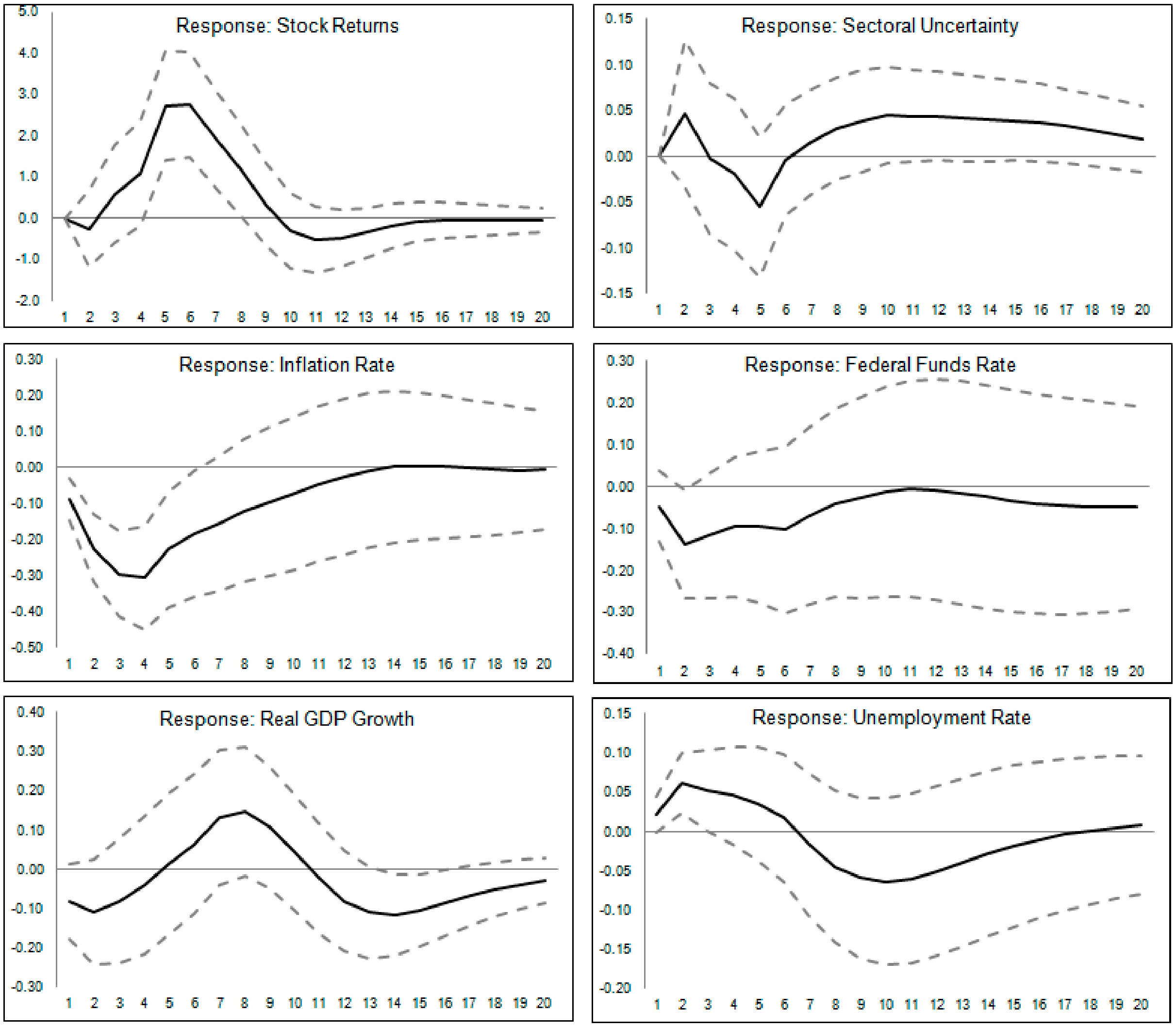


Figure 5. Response to Sectoral Uncertainty Shocks (7 Variable VAR)

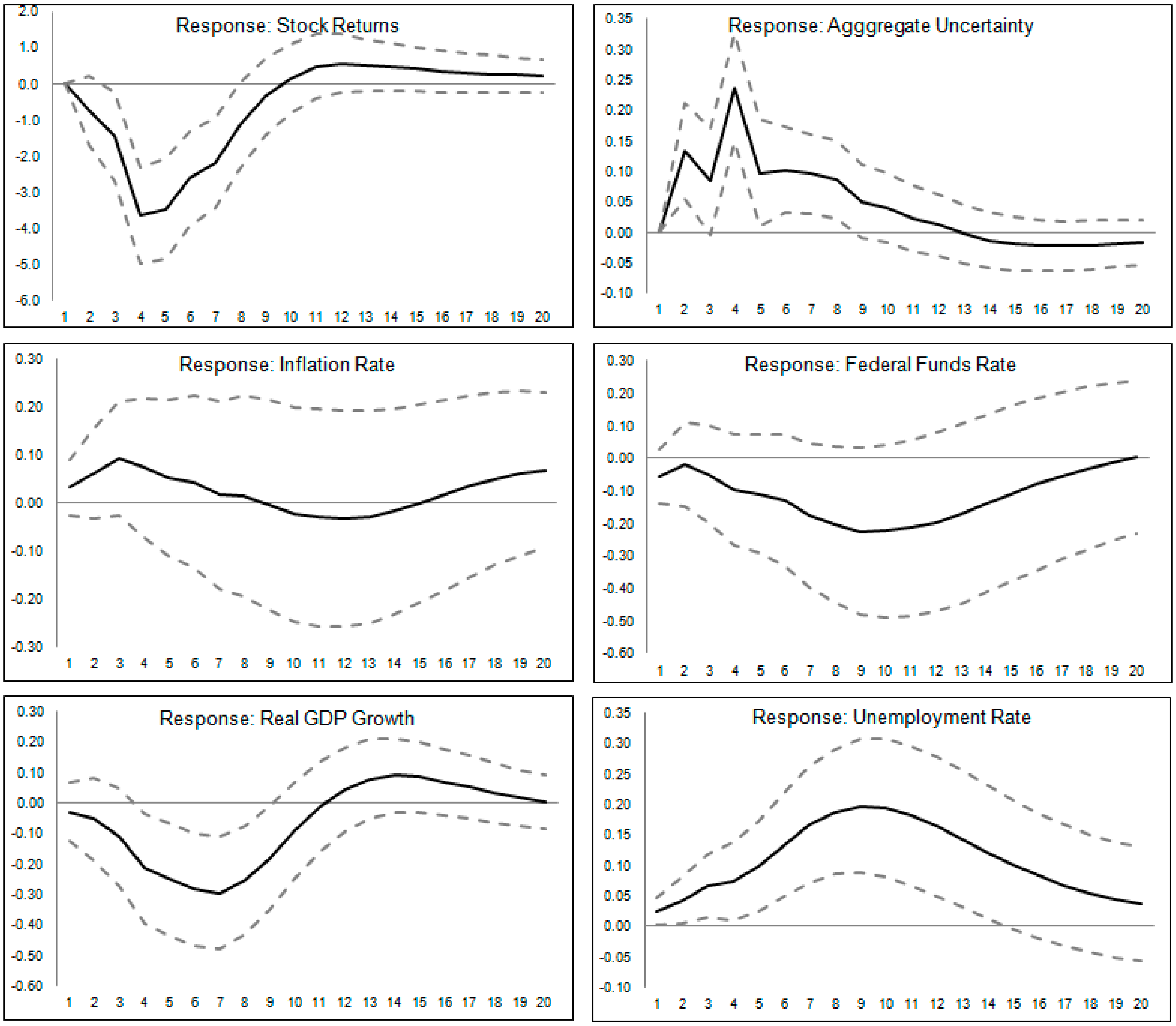


Figure 6. Forecast Error Decomposition of Unemployment Rate by Aggregate Uncertainty

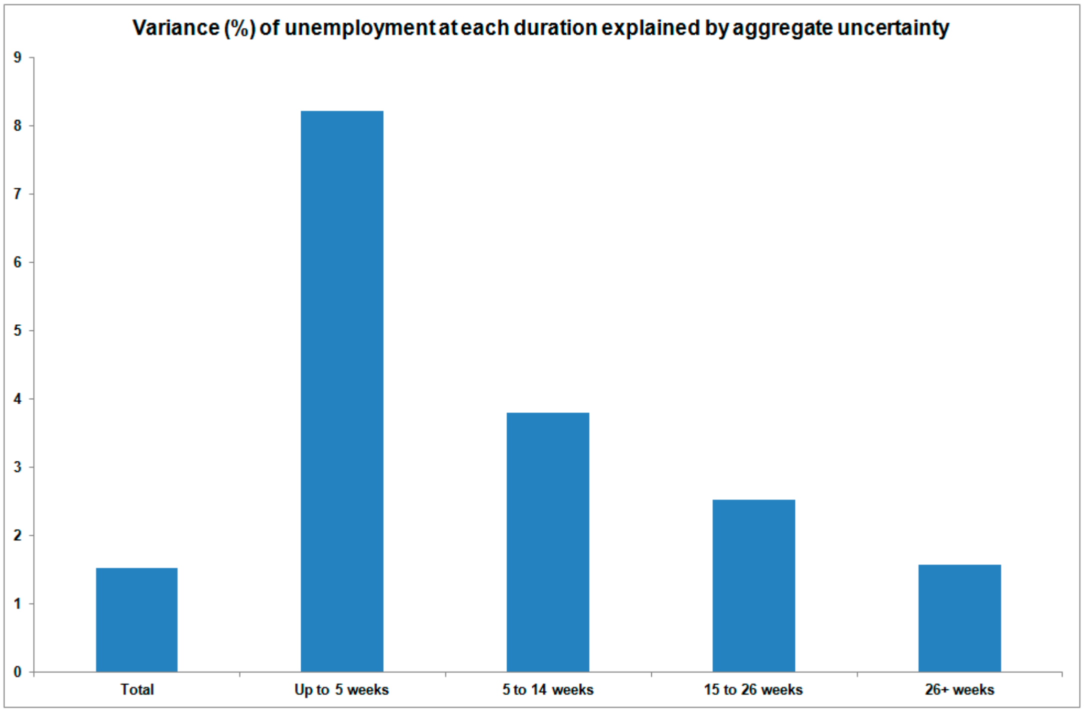


Figure 7. Forecast Error Decomposition of Unemployment Rate by Sectoral Uncertainty

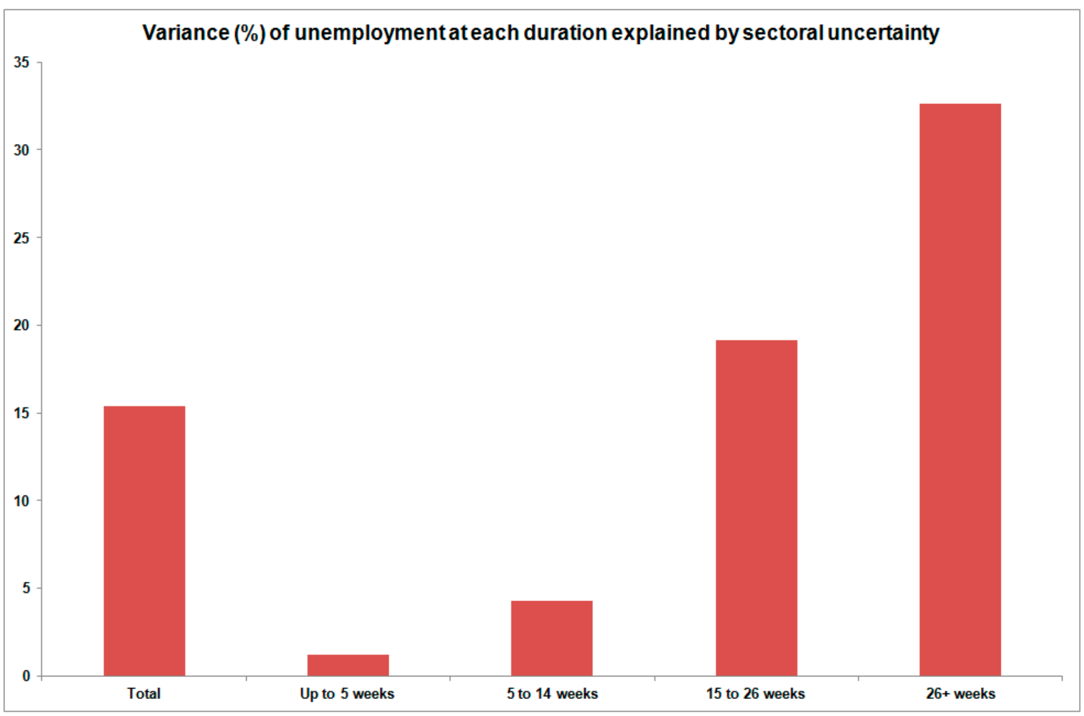


Figure 8. The Response of the Long-term Unemployment Rate to Uncertainty Shocks

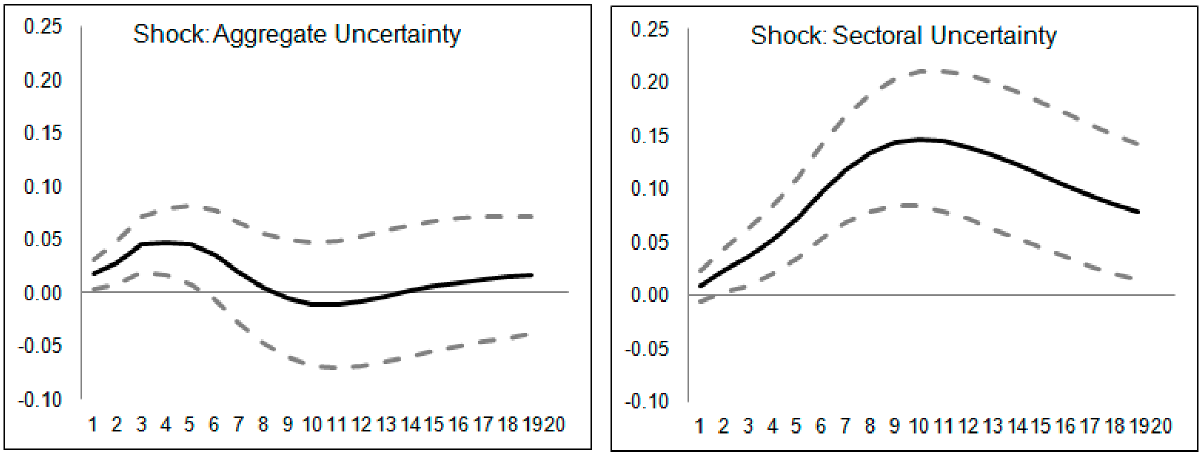


Figure 9. Contribution of Uncertainty Shocks to the Long-term Unemployment Rate during the Great Recession (%)

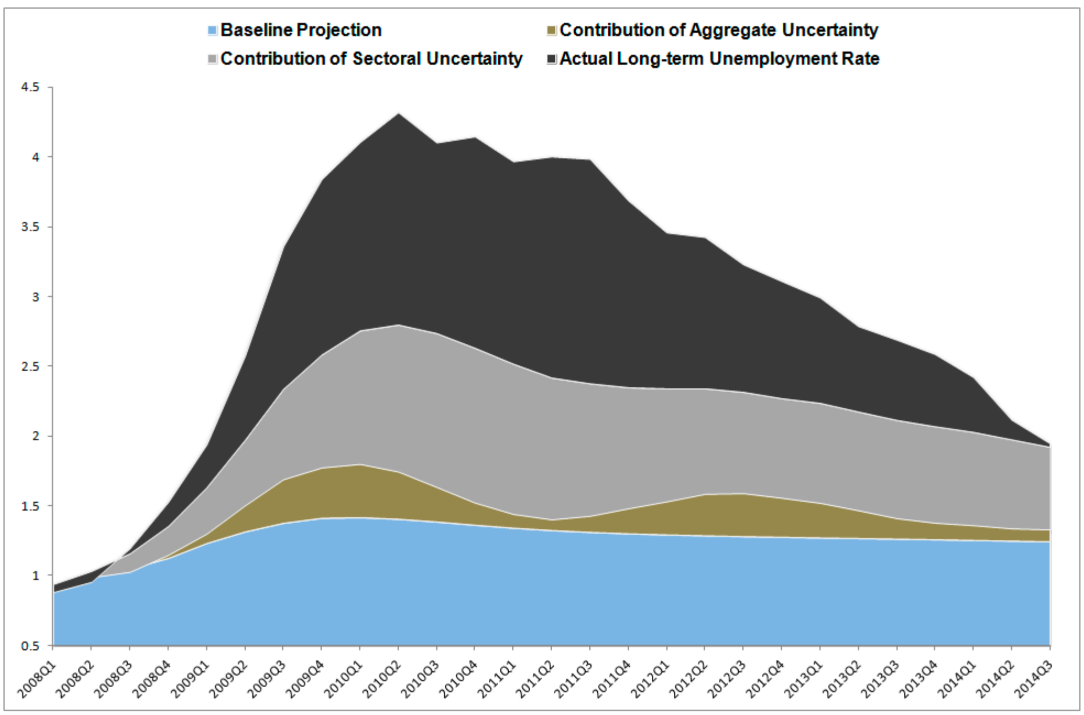


Figure 10A. Robustness Check: Estimation with Data from 1984Q1 to 2014Q3

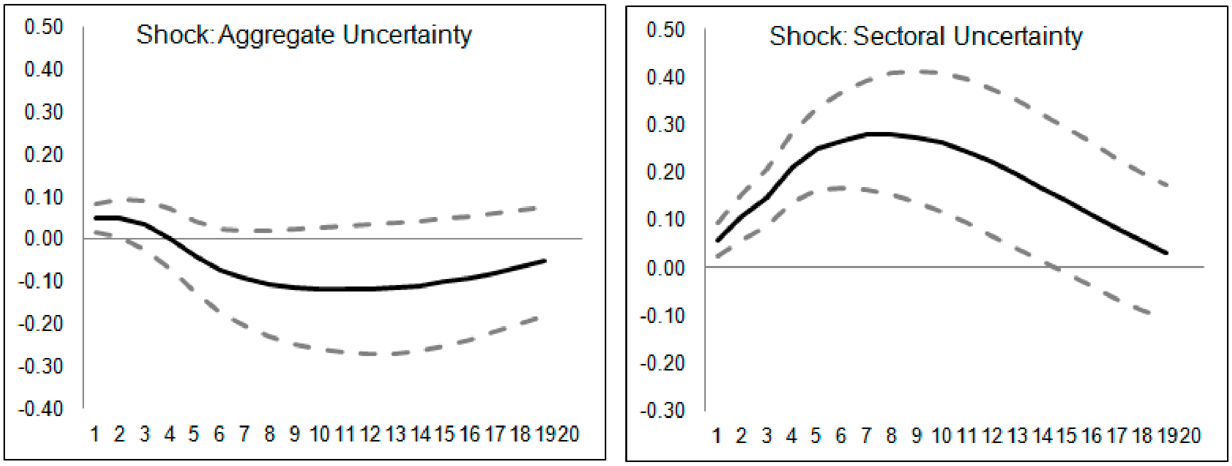


Figure 10b. Robustness Check: Estimation with Data from 1984Q1 to 2007Q4

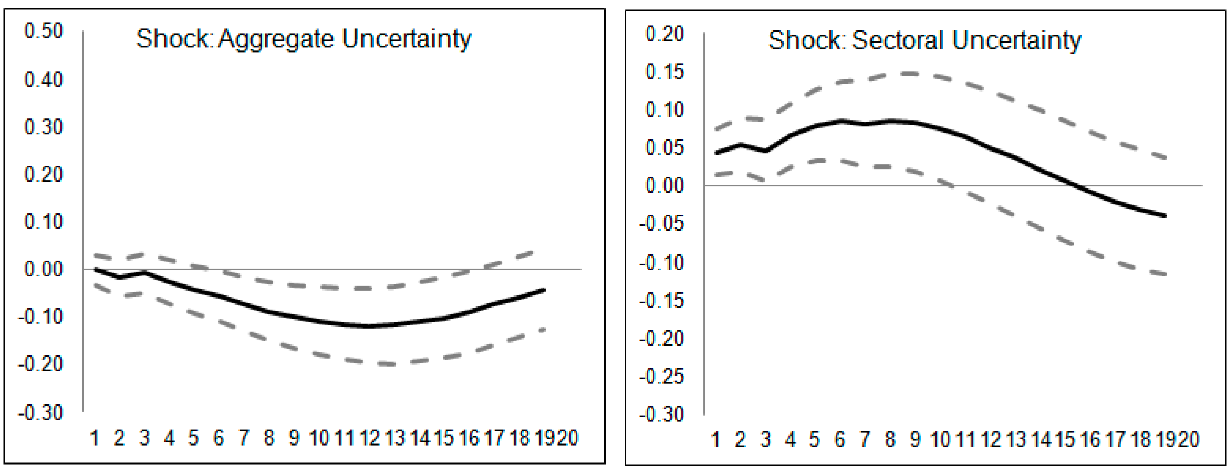


Figure 11. Robustness Check: 4 Variable VAR

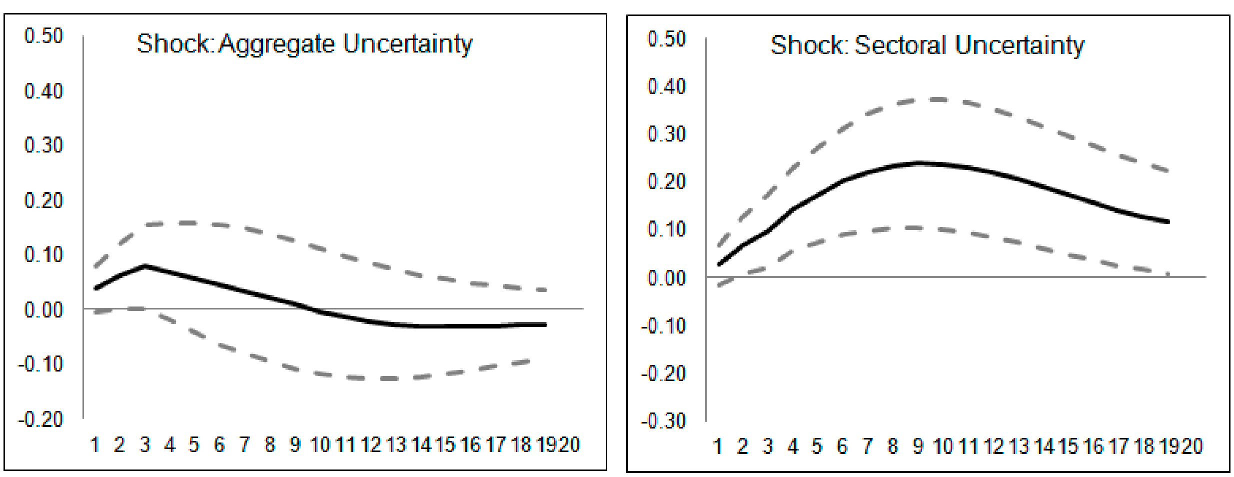


Figure 12. Robustness Check: The Reverse Ordering of the Baseline VAR System

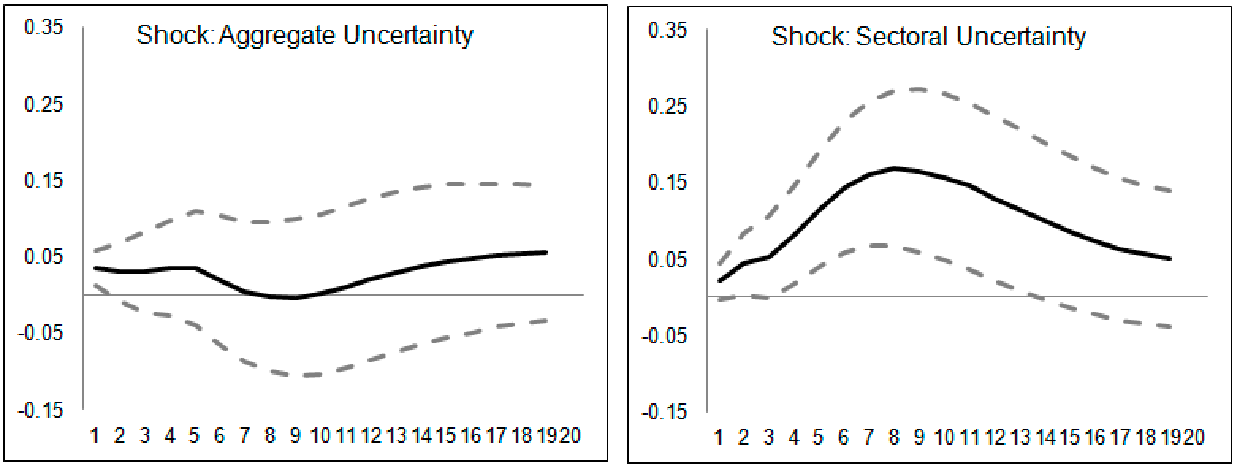
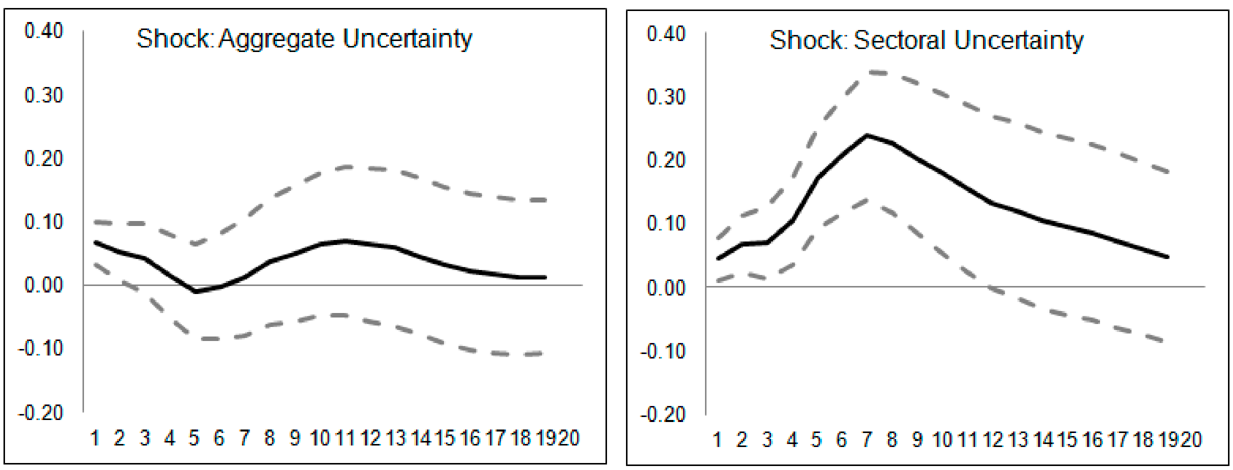


Figure 13. Robustness Check: Using 8 Lags instead of 4 Lags



APPENDIX A

Construction of the Sectoral Uncertainty Index

This section describes in detail how we construct the sectoral uncertainty index using the similar methodologies of Loungani and others (1990) and Brainard and Cutler (1993). Given the data constraints, our baseline series cover 1957Q1 to 2014Q3. This exercise presents three main challenges. First, industry subgroups are added and deleted over the lifetime of the S&P500 Composite Index, so we obtain a list of the dates of changes in the S&P.

Second, weights are based on the BLS employment data which use SIC industry codes; however, the S&P500 industry-level indexes do not correspond exactly to SIC industry codes. Therefore, we determine the weight by two-digit SIC codes and divide the weight evenly among the component industries at the end of the sample period. We match the two-digit SIC codes of individual firms with each S&P500 industry index. For example, at the end of the sample period, one S&P500 industry consists of ten firms, including six firms in one two-digit industry, three firms in another, and one firm in a third two-digit industry. We calculate the employment share of the S&P500 industry as the weighted average of the employment share of the three two-digit SIC industries for each period. In this case, the weight for each industry is 0.6, 0.3, and 0.1.

Third, disaggregated industry-level employment data are consistently available only after 1990; therefore, we use the average of employment share of two-digit SIC codes between 1990 and 2009. Our weights are not time-varying and can be subject to bias in a time trend. However, the sectoral uncertainty index based on the average employment share and the unweighted index are highly correlated. Our index contains only S&P500 industry indexes included in the composite at the end of the sample period. Among these industries, we excluded S&P500 industries added to the S&P500 Composite, resulting in 50 U.S. industries at the end of the sample period. In sum, our main results are robust when using any index because the correlation between indices based on different employment weights exceeds 0.9. Table A.1 shows the name of industry, S&P500 industry code, starting date, and employment share, when applicable.

Table A.1 - Industrial Composition of the Sectoral Uncertainty Index

SP500 Industry	SP500 Code	Starting period in GFD	Average Employment Share between 1990 and 2009 (%)	Employment Share in 2009 (%)
SP500 Oil, Gas and Consumable Fuels	101020	September 30, 1910	3.341	2.781
SP500 Oil and Gas Equipment	10112	January 31, 1941	3.330	3.554
SP500 Metal and Glass Containers	15103010	December 31, 1925	3.326	3.766
SP500 Paper Packaging	15103020	January 31, 1941	1.093	0.731
SP500 Chemicals Composite	1511	May 31, 1902	2.716	2.096
SP500 Aluminum	15141	January 31, 1935	0.461	0.284
SP500 Diversified Metals and Mining	15142	January 31, 1941	0.104	0.066
SP500 Gold	15143	January 31, 1941	0.024	0.015
SP500 Steel	15145	January 31, 1887	2.334	1.777
SP500 Paper and Forest	1515	August 31, 1898	1.034	0.591
SP500 Aerospace and Defense	201010	May 18, 1928	3.772	2.590
SP500 Machinery	201060	June 30, 1900	2.707	2.229
SP500 Building Products	2012	September 30, 1916	1.994	1.900
SP500 Electrical Equipment	2014	January 31, 1918	1.410	0.752
SP500 Environmental Services	20201050	January 31, 1965	0.135	0.172
SP500 Railroads	20304010	January 31, 1871	0.573	0.473
SP500 Air Freight and Couriers	2031	January 6, 1965	4.222	3.935
SP500 Airlines	2032	May 18, 1928	0.445	0.358
SP500 Automobiles	251020	January 31, 1912	1.225	0.987
SP500 Automobile Parts and Equipment	25111	January 7, 1970	0.513	0.472
SP500 Homebuilding	25213	January 6, 1965	1.544	1.001
SP500 Leisure Products	25221	January 6, 1965	0.645	0.397
SP500 Apparel, Accessories, Luxury Goods	25231	November 30, 1913	2.163	0.483
SP500 Footware	25232	August 31, 1915	0.688	0.340
SP500 Restaurants	25301040	January 6, 1965	11.592	15.403
SP500 Hotels, Resorts and Cruise Lines	25312	January 6, 1965	3.348	3.769
SP500 Movies and Entertainment	25413	May 31, 1919	0.213	0.226
SP500 Publishing	25414	January 31, 1941	2.830	2.778
SP500 General Merchandise	25503020	January 8, 1969	2.343	2.809
SP500 Department Stores	25531	October 31, 1909	4.555	4.802
SP500 Drug Retail	30111	January 7, 1970	3.444	3.757
SP500 Food Retail	30113	October 31, 1909	0.922	2.005
SP500 Packaged Foods and Meats	30202030	January 31, 1926	5.957	5.828
SP500 Brewers	30211	January 31, 1934	2.561	2.632
SP500 Soft Drinks	30213	January 31, 1926	0.106	0.117
SP500 Tobacco	3023	January 31, 1912	0.402	0.348
SP500 Household Products	303010	December 31, 1925	0.690	0.606
SP500 Personal Products	3032	January 2, 1957	0.605	0.524
SP500 Health Care Equipment	35101010	January 6, 1965	0.703	0.702
SP500 Pharmaceuticals	352020	November 30, 1916	3.090	3.491
SP500 Commercial Banks	4011	January 31, 1941	0.951	1.027
SP500 Consumer Finance	40221	January 31, 1935	4.205	4.462
SP500 Life and Health Insurance	40312	January 31, 1941	2.309	2.633
SP500 Multi-line Insurance	40313	January 3, 1968	1.183	1.370
SP500 Property and Casualty Insurance	40314	January 31, 1926	1.811	1.845
SP500 Computer Hardware	45202010	March 31, 1911	0.870	0.983
SP500 Semiconductors	45205020	January 8, 1969	1.444	1.801
SP500 Integrated Telecommunications	50112	January 31, 1871	2.327	2.551
SP500 Electric Utilities	551010	January 31, 1918	0.509	0.857
SP500 Gas Utilities	551020	January 31, 1941	1.071	0.789