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The Impact of Uncertainty Shocks on the UK Economy

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Abstract

This paper quantifies the economic impact of uncertainty shocks in the UK using data that span the recent Great Recession. We find that uncertainty shocks have a significant impact on economic activity in the UK, depressing industrial production and GDP.The peak impact is felt fairly quickly at around 6-12 months after the shock, and becomes statistically negligible after 18 months. Interestingly, the impact of uncertainty shocks on industrial production in the UK is strikingly similar to that of the US both in terms of the shape and magnitude of the response. However, unemployment in the UK is less affected by uncertainty shocks. Finally, we find that uncertainty shocks can account for about a quarter of the decline in industrial production during the Great Recession.

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I. INTRODUCTION

Uncertainty shocks are increasingly considered to be an important source of economic fluctuations. Although the theoretical case for the impact of high uncertainty on economic activity has been long established (see Dixit and Pindyck, 1994, for example), its role became particularly prominent during the recent global financial crisis—commonly referred to as the Great Recession—which saw sharp increases in volatility worldwide, both in stock markets and in economic activity. In the canonical option value model, firms optimally adopt a "wait-and-see" behavior when faced with high uncertainty, curtailing investment and hiring, and thus pushing the economy into recession.

Cross-country evidence on the quantitative impact of uncertainty on economic activity, however, is mixed. For example, Chugh (2011) finds that firm-level productivity risk shocks in the US manufacturing sector do not have a significant impact on GDP fluctuations, especially when compared against the impact of aggregate productivity shocks. Similarly, Bachmann and Bayer (2009), using German firm-level data, establish that time-varying firm-level risk shocks alone do not have a quantitatively large effect on business cycles. On the other hand, Bloom et al. (2011) determine that time-varying uncertainty has large consequences for the US real economy—resulting in a decline in GDP on the order of 2 percent. Moreover, the authors find that uncertainty is strongly counter-cyclical at both the industry and aggregate level, suggesting that both micro and macro uncertainty shocks exhibit a similar effect on output. Further evidence pointing to a strong negative relationship between aggregate uncertainty and economic activity comes from Arslan, et al. (2011) who bases their findings on data from Turkey.

In the case of the UK, there is some evidence that uncertainty has an important effect on economic activity. During the Great Recession, more than half of survey respondents cited uncertainty about future demand as a key factor behind their decision to limit capital expenditure plans (Figure 1). Early work by Driver and Moreton (1991) found that higher uncertainty (measured using the dispersion of output and inflation forecasts) affects investment both in the short run and in the long run.[1] More recently, Bloom, Bond and Van Reenen (2007) also find evidence that supports the claim that higher uncertainty reduces capital expenditure in UK firms. Their sample, however, stops at 1991 due to a break induced by accounting changes at that time.

In this paper, we quantify the economic impact of uncertainty shocks in the UK using data that span the recent Great Recession. Relative to the existing literature, this paper makes three contributions. First, we expand the analysis to cover a broader range of economic variables that could potentially be affected by uncertainty shocks. In particular, we measure the impact of two measures of uncertainty—the implied volatility of the stock market, and the dispersion of GDP forecasts—on industrial production, GDP, unemployment and consumer confidence. Second, we perform two comparisons of the economic responses to

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[1] The work appears to be partly in response to Bean (1989) who failed to find any relationship between uncertainty (proxied for by the variation in corporate profitability) and investment.

uncertainty shocks to gain a better understanding of the relative importance of these shocks. The first comparison is with the impact of an important source of shocks, namely, monetary policy. The second comparison is with the magnitude of responses in the US economy to uncertainty shocks of a similar nature. Finally, the third addition of this paper to the literature is an attempt at estimating the contribution of uncertainty shocks to the decline in industrial production during the Great Recession.

We find that uncertainty shocks have a significant impact on economic activity in the UK. At its peak, uncertainty shocks depress industrial production and GDP by 0.6 and 0.3 percent, respectively. Uncertainty shocks have a relatively short, and sharp, nature to their impact. The peak impact, for example, is felt fairly quickly at around 6-12 months after the shock, while the response becomes statistically negligible after about 18 months. This feature of the impact of uncertainty shocks contrasts sharply with the response of the same economic variables to monetary policy shocks where the peak impact occurs only 18 months after the shock. Interestingly, the impact of uncertainty shocks on industrial production in the UK is strikingly similar to that of the US both in terms of the shape of the response, as well as its magnitude. However, unemployment in the UK is less affected by uncertainty shocks than is the case for the US. Finally, we find evidence that point to an important role of uncertainty shocks for the UK during the Great Recession. Uncertainty shocks can account for about a quarter of the decline in industrial production over-and-above what would have been expected.

The findings in this paper have important implications for designing policy responses to deal with economic downturns. In theory, the impact of demand management policies during periods of high uncertainty are smaller than under normal circumstances, due to the fact that firms optimally behave in a more cautious manner during these periods (see Bloom et al, 2011). Thus, if a recession is found to be characterized by a high degree of uncertainty, then policy stimulus needs to be significantly large to offset the freeze on hiring and drop in output. However, to avoid overshooting, the policy stimulus needs to be cancelled once uncertainty reverts back to normal over time. Quantifying the importance of uncertainty shocks—including evidence on which measures of uncertainty are most relevant—is thus crucial.

The paper is structured in the following manner. First, we describe the two measures of uncertainty that we use. We then present the baseline model, followed by a sequence of robustness tests. The subsequent two sections compare the impact of uncertainty shocks to monetary policy shocks, and to the impact on economic variables in the US. In Section VII, we measure the impact of uncertainty shocks for the UK during the Great Recession. Finally, Section VIII concludes.

II. MEASURES OF UNCERTAINTY

We consider two measures of uncertainty. The first is the implied volatility derived from options on the FTSE-100 index, while the second measure is the dispersion of one-year ahead forecasts of GDP in the UK. Both these measures have been used before in previous studies. Stock-market volatility, for example, has been shown to have had a significant impact on durable consumption in the prewar era (Romer, 1990). Bloom, Bond and Van

Reenen (2007) show that firm-level stock return volatility is significantly correlated with a range of alternative uncertainty proxies, including real sales growth volatility and the cross-sectional distribution of financial analysts' forecasts. In the case of forecast dispersion, Kannan and Kohler-Geib (2010) show that increased dispersion of GDP forecasts is associated with a higher probability of a financial crisis in emerging markets. Driver and Moreton (1991) also use a variant of this measure to study the impact of uncertainty on investment in the UK.

Data on implied volatility of the FTSE-100 index are obtained from the Bank of England (BoE). The measure is computed using the standard Black-Scholes method (Black and Scholes, 1973) on a FTSE-100 index option contract, which if exercised at expiry, settles on the value of the FTSE-100 index prevailing at the expiry date of the option.[2] In order to avoid the effect of changes in the distance to the expiration date of the option contract on the measure of implied volatility, the BoE interpolate across implied volatilities of contracts with differing maturities. In the analysis that follows, we use the computed implied volatility based on a fixed maturity of 3 months.[3]

Table 1. Correlation Coefficients

	FTSE-100 implied volatility	Dispersion of UK GDP forecasts	Unemployment rate	Policy rate	Industrial production	Consumer confidence	NIESR's UK GDP
FTSE-100 implied volatility	1						
Dispersion of UK GDP forecasts	0.44	1					
Unemployment rate	-0.04	0.02	1				
Policy rate	0.05	-0.04	-0.86	1			
Industrial production	-0.20	-0.22	-0.65	0.54	1		
Consumer confidence	-0.24	-0.10	0.08	-0.16	0.07	1	
NIESR's UK GDP	-0.12	-0.16	-0.72	0.61	0.90	0.08	1

The second measure of uncertainty that we use is the dispersion of one-year ahead GDP forecasts, as compiled by Consensus Economics. We have monthly data of GDP forecasts from about 21-35 forecasters from October 1989 to October 2011. The forecasts that are reported, however, are for current year and following year GDP. This means that the forecast horizon changes from month to month. In January of 1995, for example, the forecast for 1995 GDP has a 1-year horizon. However, when we move to June of that year, the 1995 GDP forecast becomes a 6-month ahead forecast. To account for this, we take a weighted average of each individual forecasters current (*FC*) and next year (*FN*) forecasts to get a measure of 1-year ahead forecast (*F*1). Specifically, if we are in month *m* (where *m* runs from 1 to 12) of year *t*, the 1-year ahead forecast for investor *i* is

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[2] The contracts are European and are traded on the London International Financial Futures and Options Exchange.

[3] A broad description of the BoE's methodology (and related references) can be found at Bank of England (2000).

$$F1_{i,m} = \left(\frac{13-m}{12}\right)FC_{i,m} + \left(\frac{m-1}{12}\right)FN_{i,m}$$

(1)

The standard deviation of $F1_{i,m}$ (across all forecasters i) is our measure of one-year ahead forecast dispersion.

Figure 2 plots our two measures of uncertainty from October 1989 to October 2011. The implied volatility measure features peaks that we can associate with significant events. The peaks in the late 1990s and early 2000s, for example, coincide with the Asian Crisis/LTCM episodes and the bursting of the dot-com bubble, respectively. The onset of the global financial crisis (and subsequent Great Recession) features the sharpest spike in implied volatility during this period. Towards the end of the sample, the escalation of the debt crisis in the Euro area has also resulted in increasing uncertainty. In contrast, the dispersion measure does not have clear associations with particular events. While the measure spikes up during the same episodes as those that affected the implied volatility measure, the magnitudes do not offer a clear differentiation of the relative importance of these events. The two measures, however, are positively correlated, as shown in Table 1.

III.   BASELINE VAR MODEL

In this section, we present the results from our baseline model—a low-dimensional VAR—estimated on monthly data from June 1984 to September 2011. The baseline VAR model contains three variables: one of the two measures of uncertainty described above, the unemployment rate, and one of three economic indicators. The set of economic indicators that we consider includes the industrial production index, consumer confidence, and the monthly estimate of UK GDP constructed by the National Institute of Economic and Social Research (NIESR).[4] We start with a low-dimensional model as a baseline to avoid over-parameterization at this stage, as more variables will be added in later parts of the paper. The system is identified following the standard recursive ordering procedure with the order following the listing of the variables above. The appropriate lag-length for the VAR is chosen using the Akaike information criterion. In the next section, we will vary both the lag length and the ordering of the variables to ensure the robustness of our results.[5]

Figure 3 shows how the different variables in the system respond to an uncertainty shock, along with the associated 90 percent confidence intervals.[6] Industrial production falls

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[4] We thank Ian Hurst and Simon Kirby for providing us with this data. Table 1 shows the pair wise correlation coefficients across these various indicators.

[5] All variables (with the exception of the consumer confidence index) have been rendered stationary through the use of the Hodrick-Prescott filter with smoothness parameter,λ set to 129600.

[6] An uncertainty shock is defined as a 2 standard deviation shock. Confidence intervals are derived using asymptotic distributions. A 2 standard deviation shock is used, as this accord with the large, and arguably exogenous, volatility shocks that are more easily attributable to discrete event as opposed to the smaller ongoing fluctuations.

following a spike in uncertainty. The decline peaks at -0.6 percent 5 months after the shock, and dissipates after two years. Uncertainty shocks are also found to affect the broader measure of economic activity, as captured by NIESR's monthly GDP series. GDP falls by a peak value of 0.3 percent after 9 months followed by a gradual rebound to the baseline value after 3 years. The response of GDP to an uncertainty shock is mirrored by the response of the unemployment rate, which increases by about 0.08 percentage points a year after the spike in uncertainty. Unlike the responses of industrial production and GDP, however, the response of unemployment is not statistically significant at the 90-percent confidence level. Finally, consumer confidence falls by 1 point upon impact of an uncertainty shock, but quickly rebounds.

We next look at how shocks arising from our second measure of uncertainty—the dispersion of 1-year ahead GDP forecasts—impact the UK economy. Figure 4 plots the responses to our set of economic variables from an orthogonalized shock to the forecast dispersion measure.[7] Qualitatively, the impulse response charts match our theoretical predictions. Both industrial production and the broader measure of GDP fall following a shock to the forecast dispersion measure with magnitudes broadly similar to the impulse responses following a shock to stock market volatility. Unemployment also increases in a broadly similar path. However, standard error bands are larger. The responses of GDP to shocks to the dispersion of forecasts, for example, are not statistically significant at the 90 percent confidence level. The general finding that impulse response graphs for the forecast dispersion measure have a similar shape, but larger standard errors, compared to impulse responses for the stock market volatility measure, carries forward to the other exercises carried out in this paper. We conclude from this finding that the measure of uncertainty proxied by the dispersion of analysts' forecasts does not have a significant impact on economic activity in the UK. As such, we focus only on uncertainty shocks arising from stock market volatility in the analysis that follows.

How significant is the magnitude of responses of industrial production and GDP to uncertainty shocks? A comparison with the earlier findings of Driver and Moreton (1991) suggest that the impact is substantial. In that paper, a 2 standard deviation increase in their measure of output uncertainty leads to a long-run fall in investment of about 0.1 percent— about 1/20 of the peak impact we find for overall GDP.[8] However, this may not be an appropriate comparison due to differences in the measures of uncertainty, sample period, and estimation methodology. In order to better address this question, Sections V and VI compare the magnitudes of the impulse responses found in this section to the responses resulting from UK monetary policy shocks, and responses from a similar exercise using US data. Before we do these comparisons, however, we first perform some robustness tests in the next section.

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[7] Just as for the case of the measure based on the implied volatility of the FTSE, the shock here is calibrated to 2-standard deviations of the underlying series.

[8] Assuming a 15 percent share of investment in GDP.

IV. ROBUSTNESS TESTS

We have shown that our measure of uncertainty has a significant impact on variations in industrial production and GDP in the UK. However, it is possible that our baseline model is too parsimonious such that it falls short along some key dimensions that may be central to the results. In this section, we consider three changes to the baseline model, which serve as robustness checks: introducing variations to the mean outlook for the economy in the VAR, changing the number of lags, and switching the order of the variables.

A. Introducing average GDP Forecasts

A forceful critique of our baseline model is that periods of heightened uncertainty coincide with periods where the general outlook is also diminished. In other words, the shocks to volatility—second-moment shocks—often occurs simultaneously with first-moment shocks. What the baseline model could be capturing, therefore, is just the impact of shifts to the outlook on the economy rather than the impact due to uncertainty.

To address this concern, we include the average 1-year ahead forecast of UK GDP in the baseline VAR.[9] The average is computed in an analogous manner to how the 1-year ahead forecast dispersion was computed (see equation (1) above). Controlling for changes in the consensus outlook will help disentangle the impact of second-moment shocks—what we are interested in—from first-moment shocks.

Figure 5 plots the impulse response graphs for our expanded baseline model. The shape of the responses is similar to that of our baseline model. Interestingly, the magnitude of the responses for all the economic variables that we consider is actually much stronger in the extended baseline case. The peak response of industrial production following a shock to uncertainty, for example, is -1 percent compared to -0.6 percent in the baseline case. Also, the increase in unemployment following a shock to uncertainty is now statistically significant.

B. Changing Number of Lags

The second robustness test we undertake is to increase the number of lags in the VAR. Although we have consistently applied the Akaike criterion to select the appropriate lag length, some residual serial correlation may still be present. Taking into account the monthly nature of the data, we check that our results are robust to varying lag lengths by estimating the baseline VAR model with 12 lags. As shown in Figure 6, apart from an increased "jaggedness" in the response of the variables, the pattern of responses to an uncertainty shock are broadly similar to the baseline model estimated with an optimal lag-length criterion.

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[9] We have also estimated the model with the level of the FTSE-100 index included in the VAR. The results from Section III hold up.

C. Switching the order of variables

The final robustness exercise we do is to alter the ordering of the variables in the baseline VAR. As we have relied on a recursive methodology for identification, the ordering of the variables matter in identifying orthogonal shocks. We do this particular exercise in two ways. First, we plot the average impulse responses when the uncertainty variable is placed first, middle and at the end, thus accounting for all possible orderings for the variables. This is feasible given the low-dimensionality of the VAR. Second, we focus on the ordering that places the uncertainty variable last in the estimation ordering in order to avoid exaggerating its role.

Figures 7 and 8 show the impulse response graphs for the two exercises that we carry out. The orderings where the uncertainty measure is placed last show the weakest impact on the economic variables of interest. However, the differences are not particularly large. Indeed, when we look at the standard error bands that surround one of the orderings where uncertainty is ordered last (Figure 8), the response of industrial production to a shock to uncertainty remains statistically significant.

V. ARE UNCERTAINTY SHOCKS MORE IMPORTANT THAN MONETARY POLICY SHOCKS?

The results from the baseline model show that uncertainty shocks have a statistically significant impact on industrial production—and GDP, more generally—in the UK. But, how does the magnitude of the impact compare with that of other shocks? In particular, is the impact of uncertainty shocks smaller or larger than another important source of shocks, monetary policy shocks?

To address this question, we add a measure of monetary policy to the baseline VAR. The measure of policy that we use is the Bank of England (BOE)'s official policy rate. What defines the BOE's official policy rate has changed over time following the evolution of the BOE's monetary policy framework. For the relevant time period under consideration in this paper, the rate used is the "minimum band-1 dealing rate" until May 1997, the "repo rate" until August 2006, and "Bank Rate" from then onwards.[10] The policy rate is ordered third in the VAR such that it responds contemporaneously to shocks in uncertainty or unemployment. As before, the lag length is determined using the Akaike criterion.

Figure 9 shows the responses to a 1 percentage point increase in the policy rate. As predicted by theory, the shock to the policy rate is contractionary. Industrial production, and the broader measure of GDP, falls by a peak rate of 0.5 percent and 0.4 percent, respectively, 15 months after the shock. The profiles of the responses are very similar with the impact on both variables dissipating after 2½ years. The increase in the policy rate also increases unemployment with a peak response of 0.15 percentage points 18 months after the shock. Unlike in the case of the uncertainty shock, the response of unemployment to a policy rate

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[10] Data were obtained from Haver.

shock is statistically significant. Finally, consumer confidence falls upon impact by a magnitude of roughly 3 points.

The responses of the economic variables when hit by a policy rate shock are of a similar magnitude for industrial production and GDP compared to when they are hit by an uncertainty shock, but their shape is markedly different. Figure 10 plots the responses of the various economic variables to the respective shocks in the same chart to facilitate comparison. Two features of the respective plots stand out. First, uncertainty shocks affect the variables at a much shorter horizon than policy rate shocks. The peak impact for industrial production, GDP, and unemployment all occur 6 months after an uncertainty shock. In contrast, the peak responses of these variables only occur about 15-18 months after a shock to the policy rate. This hump-shaped response featuring long lags is a common finding in the empirical literature (see Leeper, Sims and Zha, 1996, and Sims, 1992). Second, the magnitude of the peak impact is somewhat similar for industrial production and GDP, providing evidence that the magnitude of the impact due to uncertainty shocks is substantial. However, the response of unemployment to a shock to the policy rate is significantly different from an uncertainty shock. Unemployment in the UK responds much more dramatically to a 1 percent monetary policy shock than it does to an uncertainty shock. This could be due to the larger impact on consumer confidence (and hence consumption), and also a more protracted fall in GDP, which results in a larger cumulative fall.

VI. ARE UNCERTAINTY SHOCKS LARGER IN THE U.K. VS. THE U.S.?

The analysis above has shown that uncertainty shocks have a significant impact on economic activity in the UK. Compared to the behavior of these variables in response to monetary policy shocks, uncertainty shocks have a much more rapid effect on economic activity with the impact dissipating after 24 months. A natural question that arises at this juncture is whether or not these findings are unique for the UK, or whether uncertainty shocks have similar effects in other countries.

To address this question, we perform a similar exercise as the one we have carried out above, but using data from the US. The particular specification that we use is the 4-variable VAR that has the measure of uncertainty, the unemployment rate, the policy rate and industrial production. Data on US unemployment and industrial production were obtained from the Bureau of Labor and Statistics and the Federal Reserve, respectively. We next have to find analogues for the uncertainty measure and the policy rate. In the case of the uncertainty shock, we use a series created by Bloom (2009) which is similar to the one we have constructed for the UK in that it is a combination of actual and implied volatility of stock prices. From 1962 to 1985, Bloom's series is based on the actual monthly standard deviation of the daily S&P 500 index. From 1986 onwards, the series is the VXO index of implied volatility constructed by the Chicago Board of Options Exchange. For the policy rate variable, we follow Bernanke and Blinder (1992) and use the Fed Funds rate as a measure of monetary policy. The VAR is estimated using monthly data from January 1980 to July 2008 (the last date for which we have Bloom's measure of uncertainty). As before, we use the AIC to determine the appropriate lag length.

Figure 11 shows the impulse responses for our model based on US data. Shocks to uncertainty have a significant impact on both industrial production and unemployment with peak responses being achieved around 6 months after the shock. The responses of these two variables are similar following a shock to monetary policy though the peak response occurs only 15-18 months after the shock.

There are some striking similarities between the impulse response graphs for the US and those that we found for the UK (Figure 12). The responses of industrial production, in particular, almost lie on top of each other—both the magnitude of the impact and the amount of time it takes for the peak impact to be reached are almost identical. This is a striking finding given the difference in estimation period, sectoral shares, and measure of uncertainty. For the other variables, the response plots for the UK are qualitatively similar to those of the US, though the magnitudes differ somewhat. The largest difference is in the behavior of unemployment in the UK following an uncertainty shock. While unemployment responds sharply in the case of the US, there is hardly any movement in the case of the UK. The responses of unemployment to policy rate shocks, however, are broadly the same for the US and the UK. Finally, the response of industrial production in the UK to policy rate shocks is only about half what we find for the US.

VII. THE IMPACT OF UNCERTAINTY SHOCKS DURING THE GREAT RECESSION

Industrial production in the UK registered a sharp decline of 12 percent during the Great Recession. Production subsequently recovered, but continued to remain below its peak 4 years after the crisis.

What role did uncertainty shocks have to play in the decline of industrial production in the UK during the Great Recession? Our proxy for uncertainty shocks—the implied volatility on the FTSE index—and the VAR framework presented in this paper allows us to shed some light on this question. We add the average 1-year ahead GDP forecast from consensus to the baseline model, as shifts in the mean outlook for the economy could potentially have played an important role in explaining shifts in industrial production during the Great Recession.

In order to address the question above, we do a historical decomposition of the variables in the VAR during the Great Recession. The basic idea behind this exercise is to pick a base period prior to the crisis, and use the VAR model to forecast subsequent movements in industrial production. The difference between the actual outturn and the forecast can then be attributed to shocks originating from one of the variables in the system. We elaborate on the methodology below.

We first start with the infinite-order moving-average representation of our 4-variable VAR process, which can be written as follows:[11]

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[11] The following discussion is based on Fackler and McMillin (1998) and Lutkepohl (2005).

$$y_t = \mu + \sum_{i=0}^{\infty} \Phi_i u_{t-i}$$

$$(2)$$

In the equation above, y_t is the 4x1 vector of the endogenous variables, μ is the vector of mean values and u_t is the vector of reduced-form error terms. The moving average coefficient matrices, Φ_i, can be determined recursively from the estimated coefficient matrix of the VAR system.

We can subsequently transform equation (2) into a moving-average representation that is composed of orthogonalized, or structural, shocks using the lower triangular Cholesky decomposition of the variance-covariance matrix of the reduced-form residuals, P.[12] Specifically, we have

$$y_t = \mu + \sum_{i=0}^{\infty} \Phi_i P P^{-1} u_{t-i} = \mu + \sum_{i=0}^{\infty} \Theta_i w_{t-i}$$

$$(3)$$

where the new moving-average coefficient matrix $\Theta_i = \Phi_i P$, and the structural shocks $w_t = P^{-1} u_t$. For any particular period $t+j$, then, the equation for the vector y can be written as

$$y_{t+j} = \sum_{i=0}^{j-1} \Theta_i w_{t+j-i} + \left(\mu + \sum_{i=j}^{\infty} \Theta_i w_{t+j-i} \right).$$

$$(4)$$

Equation (4) provides a useful framework for decomposing movements in the endogenous variables of our VAR system into contributions from the structural shocks. The bracketed term on the far right of the equation is the conditional expectation of y_{t+j} at time t. This will serve as our baseline projection of the vector y. The difference between the baseline projection and the realization of y is then captured by the first term on the right-hand side of the equation, which is a linear combination of the structural shocks between time t and $t+j$.

We use the framework developed above to investigate the role of uncertainty shocks in explaining the fall in industrial production during the Great Recession. The base period, t, is chosen to be December 2007—before the start of the recession in the second quarter of 2008. The forecast horizon extends to September 2011, the last data point in our sample.

Figure 13 plots the detrended industrial production, the baseline forecast, and the contributions of the uncertainty and mean forecast shocks. The baseline projection is the conditional expectation of industrial production over these 45 months as of December 2007. In other words, it is the VAR's forecast of industrial production as of December 2007. For the first 9 months of the forecast horizon, industrial production remained close to the baseline projection. Subsequently, however, industrial production fell dramatically. At its trough in the first half of 2009, industrial production was more than 6 percent lower than the baseline value.

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[12] $\Sigma_u = PP'$ where Σ_u is the variance-covariance matrix of the reduced-form residuals.

The two other shaded areas in the chart shows what the VAR's forecast of industrial production would have been if the orthogonalized shocks over the period January 2008 - September 2011 had been known at the end of 2007. Shocks to the mean outlook turn out to be quite important in explaining the departure of the realized industrial production from the baseline forecast. From November 2008, when industrial production first dips below trend up until July 2010, when it crosses its trend again, shocks arising from the mean GDP forecast accounted for 59 percent of the difference between the actual industrial production and its baseline projection. However, the contribution of shocks to uncertainty is also significant, with an average contribution of 23 percent during the same period. As uncertainty shocks began to fade away towards the end of 2010, industrial production also rebounded.

VIII. CONCLUSION

We have shown that uncertainty shocks, as measured primarily by the implied volatility of the FTSE-100, have a substantial impact on economic activity in the UK. The peak impact of shocks affects industrial production and GDP fairly quickly around 6-12 months after the shock, and dissipates after about 18 months. This response contrasts sharply with the response of the same variables to monetary policy shocks where the impact is more drawn out. Interestingly, the response of industrial production in the UK to uncertainty shocks is strikingly similar to that of the US both in terms of the path of the response, and its magnitude. However, unemployment in the UK is less affected by uncertainty shocks than is the case for the US. Finally, an examination of the Great Recession shows that uncertainty shocks account for about a quarter of the decline in industrial production that took place over this period.

In this paper, we have taken a fairly agnostic view on the sources of uncertainty shocks. While we have purged the impact of movements in GDP on uncertainty, the residual shocks could be due to a variety of sources, both domestic and international. Identifying the source of these shocks will be important in designing the appropriate policy response at that juncture. It is important, however, that policy itself is not a source of uncertainty. Baker, Bloom and Davis (2012), for example, find that policy-related uncertainty accounts for an increasing share of overall economic uncertainty over the past decade (see also Fernandez-Villaverde et al., 2011). Adhering to clearly articulated state-contingent policy frameworks is crucial in this regard.

As this paper has focused on the impact of aggregate uncertainty shocks, further research would be useful in isolating the specific channels through which these shocks affect household and firm behavior. One puzzle in particular that we found in this paper is the lack of responsiveness of unemployment to uncertainty shocks.[13] This contrasts with the experience in the US, as illustrated in the paper. We suspect that the relatively large employment in the public sector, or the trend decline in the UK's unemployment rate over the sample may have a role to play, but clearly more research is warranted.

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[13] This anomaly persists even if the employment series is used.

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X. TABLES

Table 1. Correlation Coefficients

	FTSE-100 implied volatility	Dispersion of UK GDP forecasts	Unemployment rate	Policy rate	Industrial production	Consumer confidence	NIESR's UK GDP
FTSE-100 implied volatility	1						
Dispersion of UK GDP forecasts	0.44	1					
Unemployment rate	-0.04	0.02	1				
Policy rate	0.05	-0.04	-0.86	1			
Industrial production	-0.20	-0.22	-0.65	0.54	1		
Consumer confidence	-0.24	-0.10	0.08	-0.16	0.07	1	
NIESR's UK GDP	-0.12	-0.16	-0.72	0.61	0.90	0.08	1

XI. FIGURES

Figure 1. Reasons for Limits to Capital Expenditure

Figure 2. Measures of Uncertainty
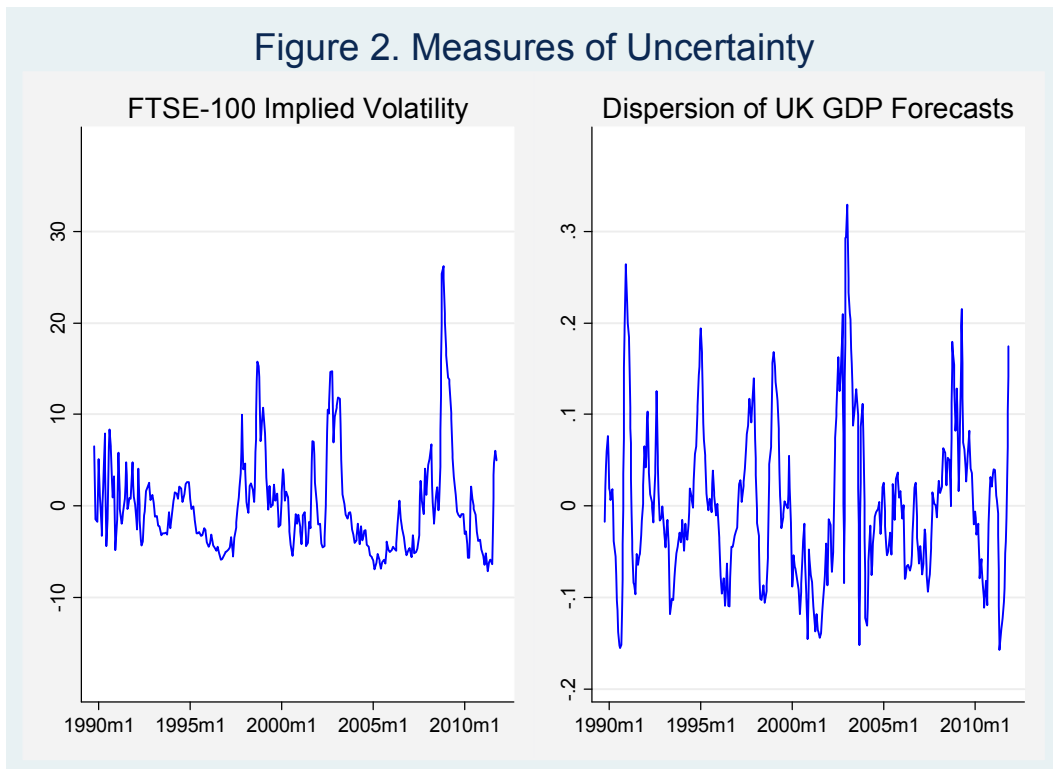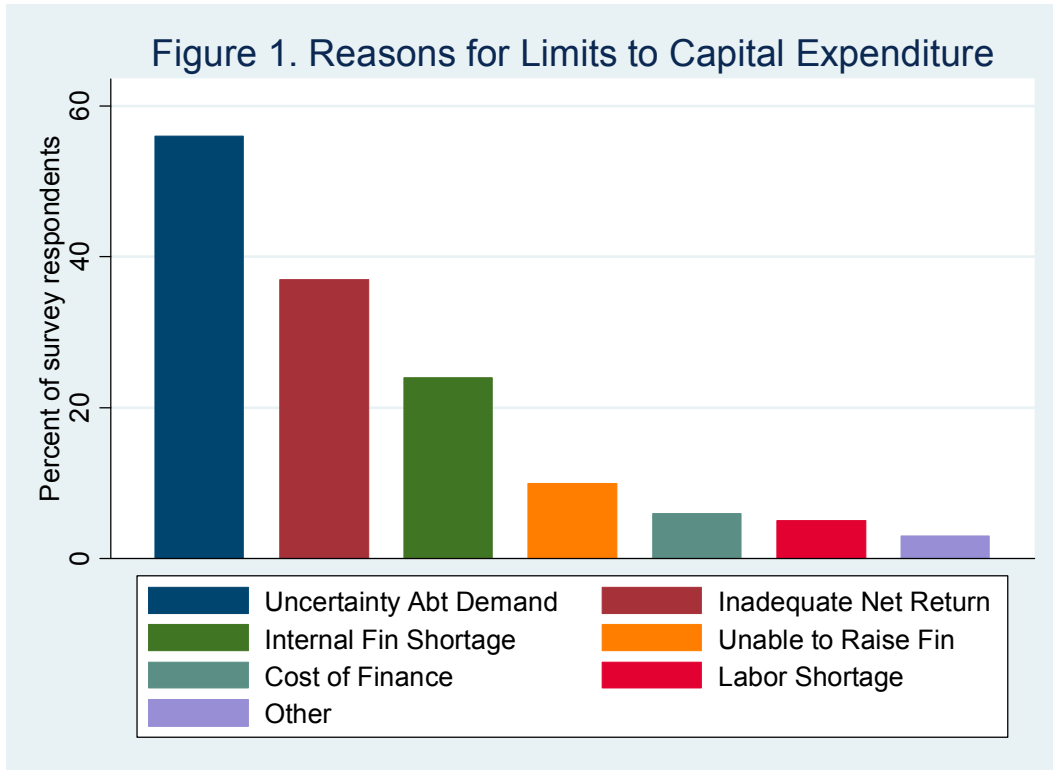
Figure 3. Response to Uncertainty Shock

Response: Ind. Prod.

Response: Unemployment

Response: GDP(NIESR)

Response: Cons. Confidence
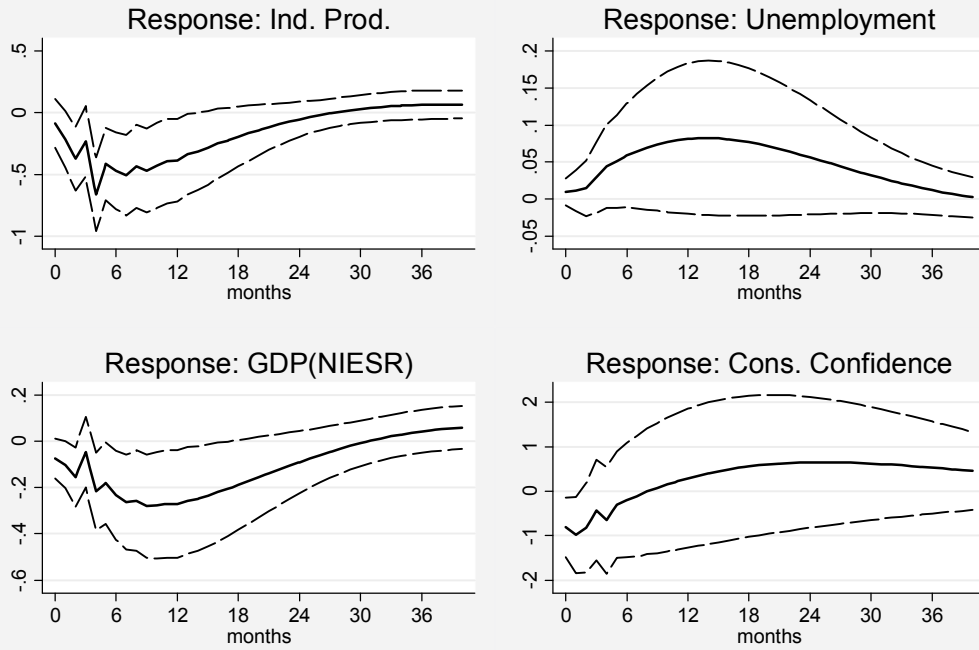
Figure 4. Response to Dispersion Shock

Response: Ind. Prod.

Response: Unemployment

Response: GDP(NIESR)

Response: Cons. Confidence
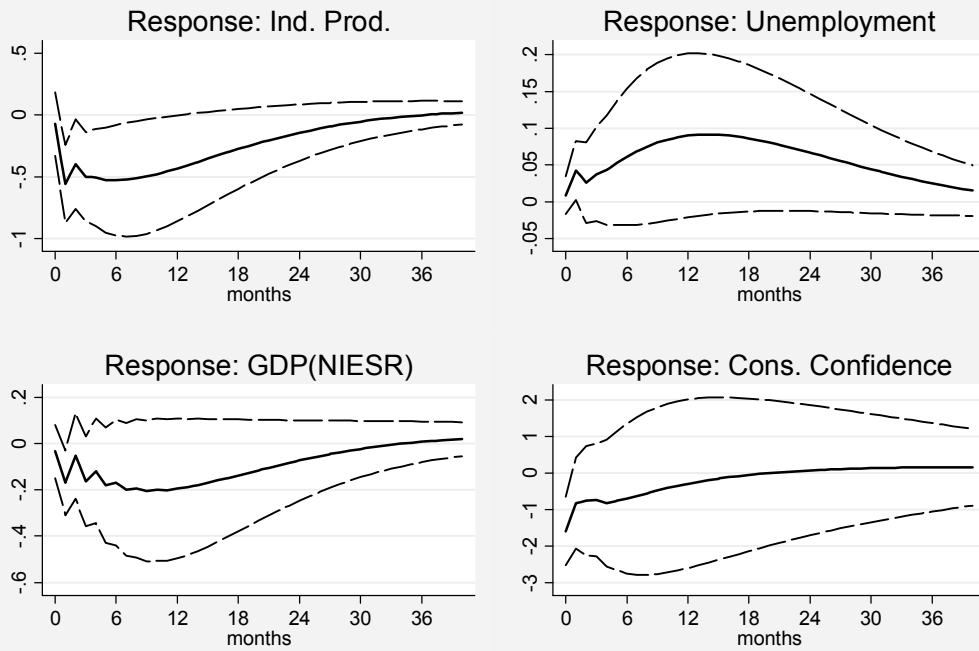
Figure 5. Response to Uncertainty Shock (with GDP forecast)

Response: Ind. Prod.

Response: Unemployment

Response: GDP(NIESR)

Response: Cons. Confidence
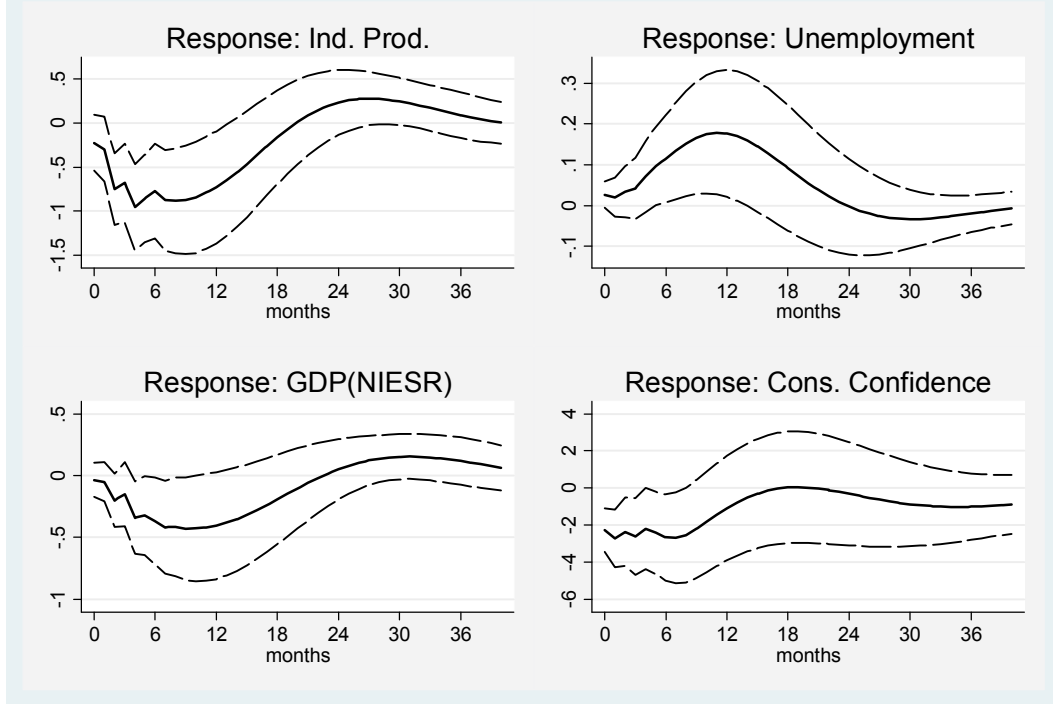
Figure 6. Response to Uncertainty Shock (12 lags)

Response: Ind. Prod.

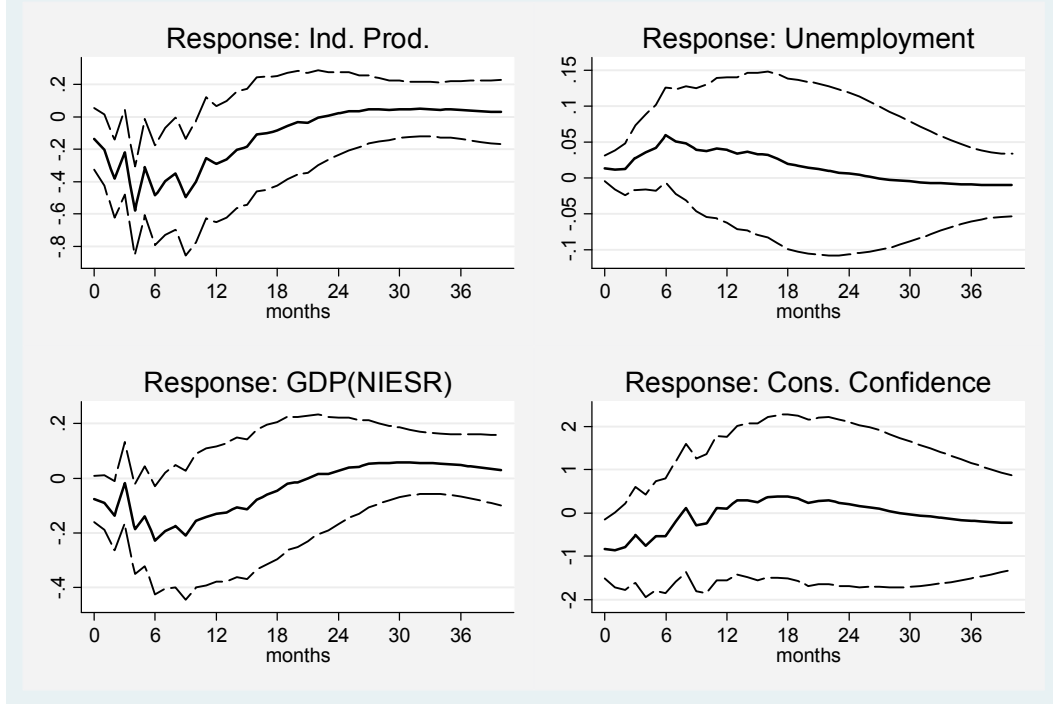Response: Unemployment

Response: GDP(NIESR)

Response: Cons. Confidence

Figure 7. Response to Uncertainty Shock (orderings)
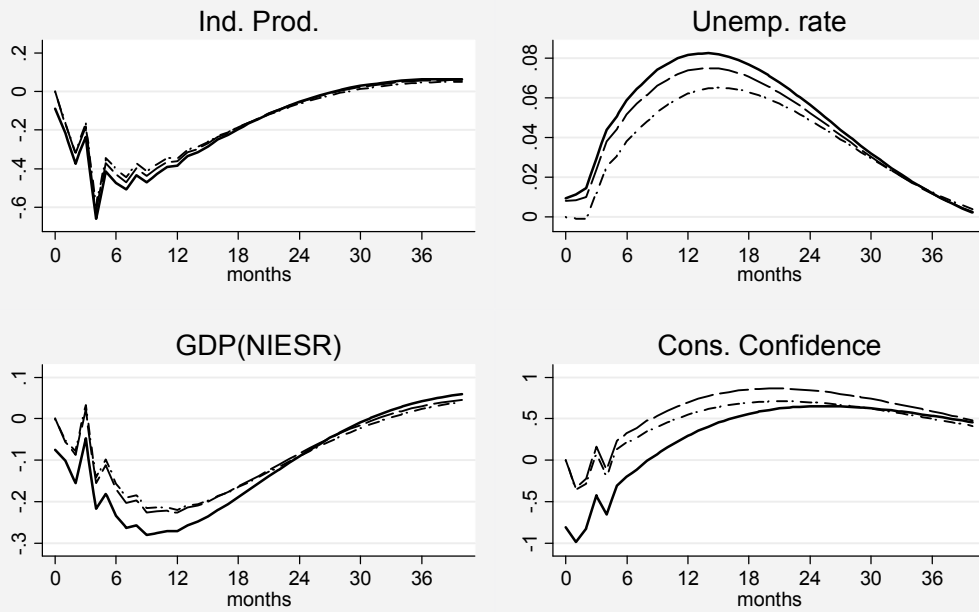### (Baseline = solid line; Middle = dash line; Last = dot-dash line)

Ind. Prod.

Unemp. rate

GDP(NIESR)

Cons. Confidence

Figure 8. Response to Uncertainty Shock

Response: Ind. Prod.

Response: Unemployment

Response: GDP(NIESR)

Response: Cons. Confidence

Figure 9. Response to Policy Rate Shock

Response: Ind. Prod.
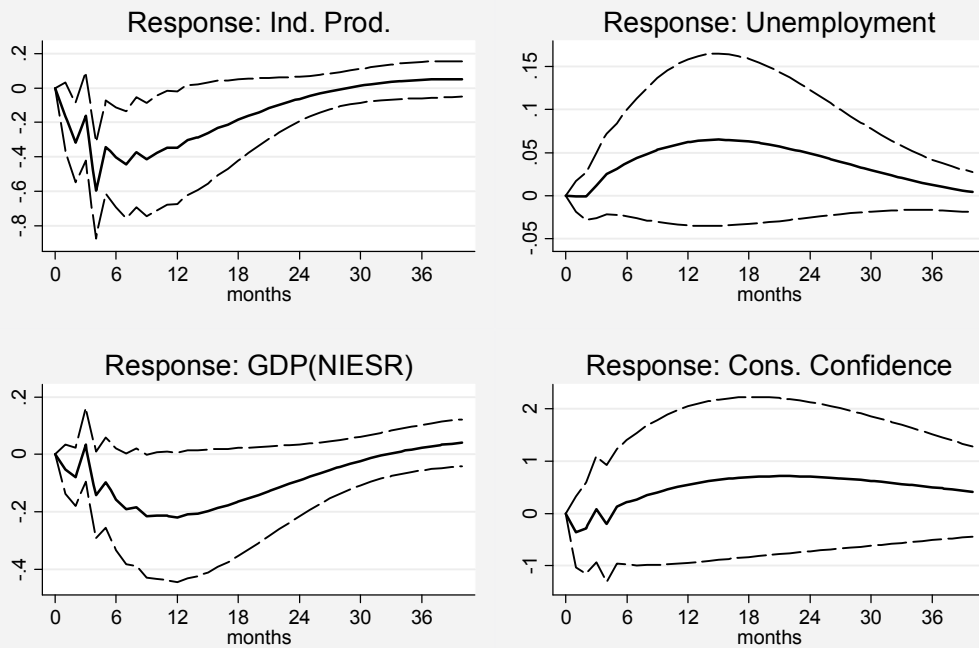

Response: Unemployment
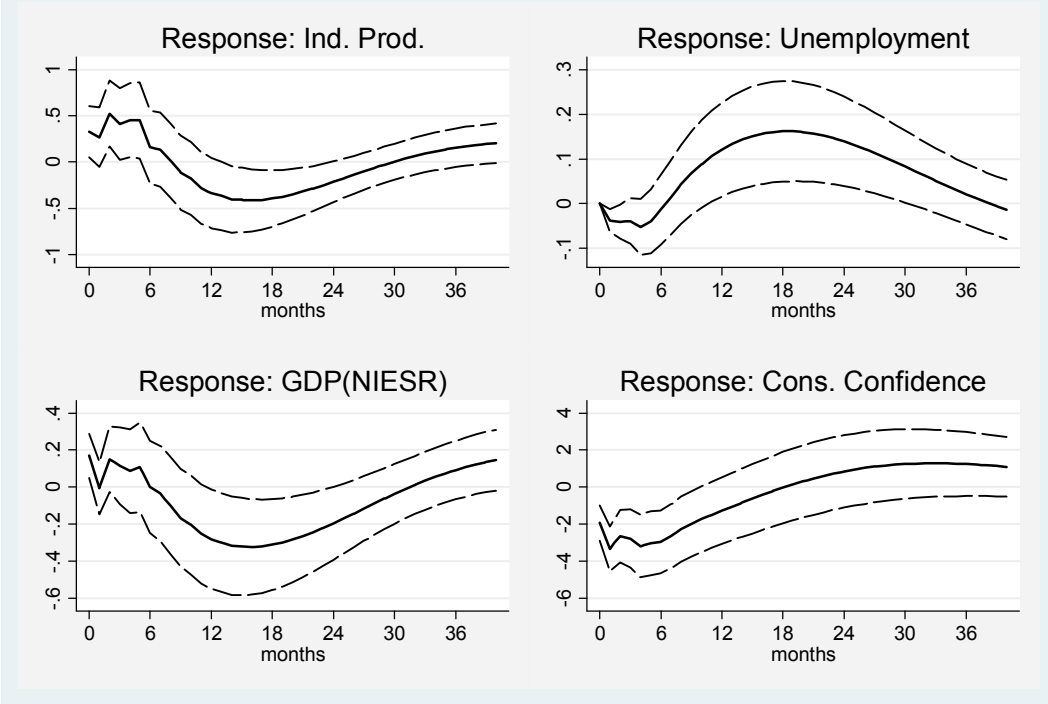

Response: GDP(NIESR)

Response: Cons. Confidence

Figure 10. Uncertainty vs. Policy Rate Shocks

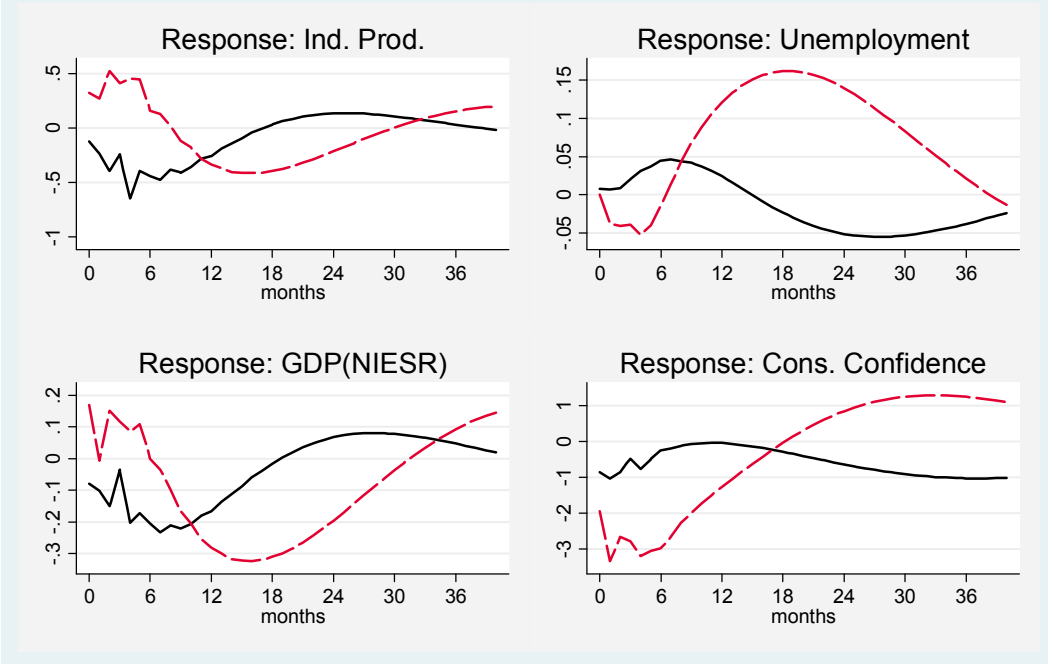(Uncertainty shock = solid line; Policy rate shock = dashed line)

Response: Ind. Prod.

Response: Unemployment

Response: GDP(NIESR)

Response: Cons. Confidence

Figure 11. Uncertainty Shocks in the U.S.

Imp:Unc., Res:IP

Imp:Unc., Res:Unemp.

Imp:FFR, Res:IP
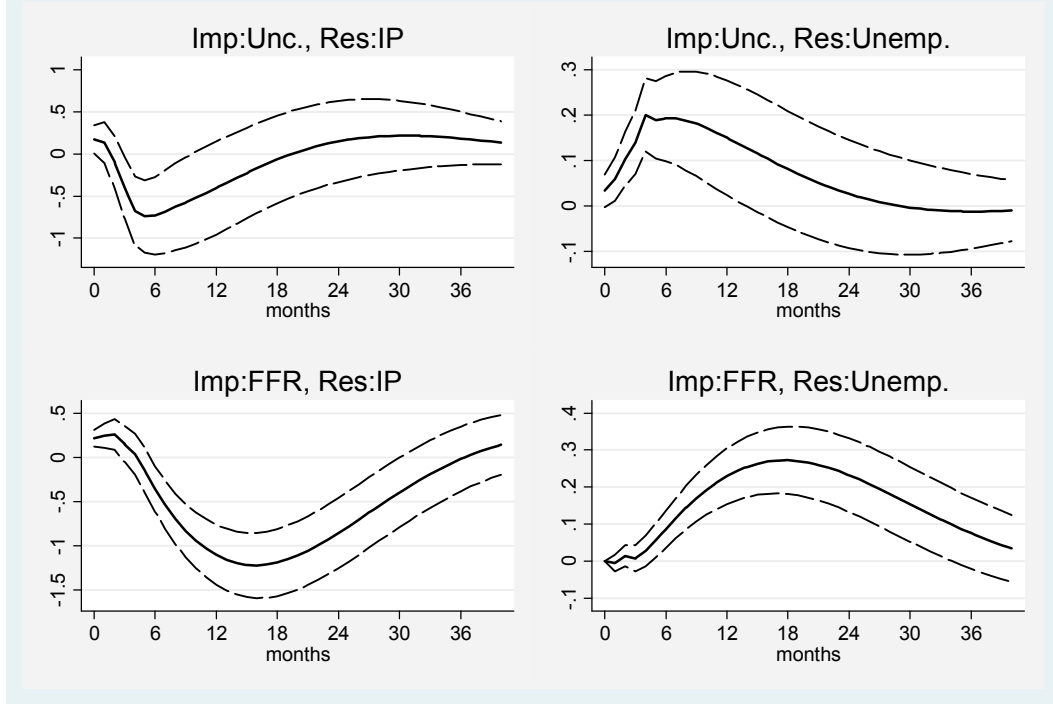
Imp:FFR, Res:Unemp.

Figure 12. Impulse-Responses for the UK & US
(UK Responses = solid line; US Responses = dashed line)

Imp:Unc., Res:IP

Imp:Unc., Res:Unemp.

Imp:Pol. Rate, Res:IP

Imp:Pol. Rate, Res:Unemp.

Figure 13. Decomposition of UK Industrial Production during the Great Recession