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Uncertain Times, uncertain measures

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Abstract

Are uncertainty shocks an important source of post WWII business cycle fluctuations? The evidence we present in this paper suggests they are. Using both the traditional measure of uncertainty – the stock market volatility index – and a new one - based on the number of New York Times' articles on uncertainty and economic activity - we demonstrate that these shocks generate short sharp recessions and recoveries. Output, employment, productivity, consumption and investment all decrease in response to an unanticipated rise in uncertainty. Moreover, we find that wide spread changes in the level of uncertainty captured by our new newspaper index can account for between 10 and 25 percent of the short-run variation in these variables.

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Introduction:

Deep recessions have at least one positive side effect – they rekindle interest in business cycle research. And with good reason since an ability to pinpoint the source of cyclical fluctuations enhances our ability to mitigate their impact and intensity. This is of particular importance today since attempts in recent years to identify the root causes of swings in economic activity have yielded decidedly mixed results. In real business cycle models, technology or productivity shocks are often the primary source of cyclical ups and downs. Despite vigorous efforts to provide empirical support for this position, a large number of economists including Gali (1999), Gali and Rabanal (2004), Francis and Ramey (2005), and Christiano, Eichenbaum, and Vigfusson (2003) maintain that only a small fraction of the fluctuations can be attributed to technology shocks.[1] In light of these findings, other candidates have been nominated as primary drivers including monetary shocks, (see e.g.,Christiano, Eichenbaum and Evans (2005, 1997), Romer and Romer (1989, 2004), Sims and Zha (1995)), fiscal shocks (Christiano and Eichenbaum (1992), Ramey and Shapiro (1998), and Blanchard and Perotti (2002), oil shocks (Hamilton (1983), Cavallo and Wu (2006)) and news shocks (Beaudry and Poitier (2006), Jaimovich and Rebelo (forthcoming)).[2] However, while each of these has a non-trivial impact, none have been found to fit the bill entirely.

[1] Although Fisher's (2006) findings suggest a significant role for investment specific technology shocks, Gali and Rabanal (2004) contend that his findings depend on the log of hours worked being a stationary process.

[2] Also, see Alexopoulos (2008) and Alexopoulos and Cohen (forthcoming) for publication based measures of technology change.

In a recent article, Bloom (forthcoming) argues that jumps in uncertainty in response to major economic or political shocks (wars, terrorist attacks, the collapse of Lehman Brothers) lead to a rapid drop and equally swift rebound in output and employment. Although he does demonstrate that large uncertainty shocks can cause recessions he does not detail in this paper the contribution of these shocks to post war business cycles nor does he empirically attempt to pin down their impact on consumption and investment (variables that many have argued are highly susceptible to uncertainty).[3]

Our first objective follows directly from these observations. We attempt to show that these shocks do account for a non-trivial share of cyclicality in the United States economy in the period 1962-2008, the time span covered by Bloom (forthcoming). Moreover, we demonstrate that consumption and investment expenditures do respond to uncertainty shocks as Bloom (forthcoming), Romer (1990) and Bernanke (1983) would have us believe.

We are motivated by an additional consideration. It is commonplace among those who try to link economic downturns to increases in uncertainty to use stock market volatility, as Bloom (forthcoming) does, to measure uncertainty.[4] The problem, of course, is that such a narrow indicator may fail to capture the full the impact of uncertainty shocks on the broader economy - the preoccupations of Wall Street may not accurately reflect the concerns of Main Street. The

[3] In a recent related paper, Bloom, et al. (2009) presents a model with uncertainty shocks that is able to account for the responses reported in Bloom (forthcoming).

[4] See, for example, Romer (1990), Bernanke (1983), Leahy and Whited (1996), Bloom, Bond, and Van Reenen (2007), Greasely and Madsen (2006).

usual response to this observation is that even individuals who do not invest in the stock market are likely to use its ups and downs as a guide to the state of the economy.[5] A natural question follows from this: how does the average citizen learn about and comprehend the implications of stock market volatility? The answer, we would argue, is, for the most part, through the media – the media is, in effect, the messenger - which suggests that a newspaper based indicator should provide a broader based measure of aggregate uncertainty than stock market volatility.[6] Our second objective, then, is to employ a just such an index to accomplish two tasks: to determine, first, the robustness of the results concerning the impact of uncertainty shocks on cyclical fluctuations and, second, to document differences in the explanatory power of the two indicators.[7]

Although some may consider our newspaper based approach to identifying uncertainty shocks unorthodox, in fact it is similar methodologically to Romer and Romer's (1989, 2004) use of narrative to identify monetary policy shocks, Ramey and Shapiro's (1998) and Ramey's (2008) reliance on magazines and newspaper to pinpoint fiscal policy shocks, Romer and Romer's (2008) use of presidential addresses, executive branch documents and Congressional papers to study the effects of tax changes, Cavello and Wu's (2006) employment

[5] See Romer (1990).

[6] Doms and Morin (2004) outline in more detail the role the media plays in informing agents about the economy.

[7] See also Alexopoulos and Cohen for a study using indicators based on a wide range of newspapers to explore the long run implication uncertainty and the role it played in determining the path of the economy in the 1930s.

of trade journals to identify exogenous oil price shocks and Doms and Morin's (2004) study explores the linkages between media coverage of economic events, consumers' perceptions, and economic outcomes. Our use of the New York Times to measure shocks has an extensive pedigree among Macroeconomists, and is used extensively in Ramey (2008) and Doms and Morin (2004). Moreover, it is an ideal vehicle for our purpose since it is, in effect, the unofficial national newspaper of record in the U.S. and is regularly read by both business men and average citizens.[8] Finally, the Economist' in its quest for a straight forward business cycle indicator uses the Times as the principle source of its R-Word indicator.

Some may worry about the direction of causality and thus question the usefulness of our index. That is, do newspaper articles raise the level of uncertainty among the general population or do they merely reflect the temper of the times?[9] We would argue that, for our purposes, the answer to this question is irrelevant. The newspaper index is nothing more than a representation of the degree of uncertainty felt by households, firms, consumers, and producers. While it may be interesting to know if the media is both the messenger and creator of the message, this knowledge has no affect on the quality of our index.

Our results can be summarized as follows. We use bi-variate and multi-variate VAR equations estimated with monthly data for the period 1962-2008 to determine the impact of the two measures of uncertainty on cyclical fluctuations in industrial production, employment,

[8] Although we focus on the New York Times, as we show in Alexopoulos and Cohen (2009), the patterns of articles on uncertainty and the economy is similar to those captured by other major newspapers.

[9] The same issue could also be raise about the stock market volatility measure.

unemployment, labor productivity, consumption, and investment. We find that the uncertainty shocks identified by both indices are able to produce significant recessions. Within the year following a positive uncertainty shock, industrial production, and employment fall, as does our measure of business investment and consumption. Further, although we cannot estimate the impact of uncertainty shocks on total factor productivity at a monthly level due to the lack of appropriate data, the responses of our monthly indicators of labor productivity are consistent with the predictions of the models present in Bloom (forthcoming) and Bloom et al (2009). Specifically, there is evidence that while productivity decreases during the first year, it overshoots its normal level for approximately a year by year three. Moreover, our findings confirm those of Bernanke (1983) and Leahy and Whited (1996) with regard to investment and those of Romer (1990) and Greasley, Oxley, and Madsen (2006), and Greasley and Madsen (2001) with respect to consumption.

We also observe some notable differences between the results obtained using the two measures. First, the Main Street uncertainty index (i.e., our newspaper measure) accounts for a larger share of the ups and downs in output and employment than the Wall Street one (i.e., the volatility measure), a result consistent with the idea that the former is a more comprehensive measure of uncertainty than the latter. Second, the Main Street indicator appears to be associated with longer downturns and more protracted rebounds than those limited to Wall Street, again, we believe, an indication that the Main Street measure is more broadly based than the Wall Street one. Changes in the level of uncertainty – especially the type that affects both Main Street and Wall Street - are, in short, a key contributor to business cycles.

The remainder of the paper is organized as follows. In section 2 we describe our new data set and compare it with the monthly indicators of stock market volatility. In section 3, we review the results of our regressions, and in section 4 we summarize our findings and offer suggestions for future research.

Section 2: Measuring Uncertainty

The Measures:

In this section, we employ two indicators of uncertainty, Bloom's stock market volatility index (ln(Vol)) as set out in his forthcoming paper and a monthly version of our New York Times uncertainty measure (ln(NYT)) developed in Alexopoulos and Cohen (2009). We describe first Bloom's index, depicted in Panel A of Figure 1. It is based on a compilation of the actual volatility of the Standard and Poor (S&P) 500 for the period pre-1986 and the VXO, the implied volatility index of the S&P 100 30 day options of the CBOE post-1986. Because of the nature of its provenance, we call it the Wall Street index. In his paper, he uses this series to identify the dates of major uncertainty shocks – also displayed in Figure 1 – and constructs his volatility indicator such that it takes a value of one for each of these shocks and a zero otherwise. While perfectly adequate for his purpose, we use in this paper his actual his actual, as opposed to his 0/1 series, for two reasons. First, as he notes in his technical appendix, the differences in the impulse responses generated by the two are minor. Second, as we want to compare the ability of the two indicators to explain the full range of cyclicality during this period, that is, the impact of both large and small uncertainty shocks on economic activity, it makes sense to use the actual series since it captures, as does our newspaper index, the full range of shocks.

In Panel B of Figure 1, we present our monthly New York Times uncertainty index which represents the total number of articles appearing each month in the newspaper that contain references to uncertainty and the economy.[10] We use the New York Times for our article count for a number of reasons. First, as we demonstrate in Alexopoulos and Cohen (2009), yearly indices for the period 1929-2008 based on these articles do coincide with periods of economic uncertainty and do have a significant impact on economic activity. Second, as the unofficial national newspaper of record for the U.S., the Times attracts a wide readership across a broad spectrum of the population. It is currently the country's third largest newspaper in terms of paid subscription, with an average daily weekday circulation of 1, 000,665, and 1,438,585 on Sunday.[11] Its website, one of the most popular online, received over 20,068,000 unique visitors in September 2008.[12] Finally, there is evidence (see Table 1) that articles in the Times are representative of what is reported in other papers.[13] In short, not only does it contain "All the news that's fit to print", it also disseminates the message far and wide.[14]

[10] Specifically we identify articles that contain the keywords (uncertain or uncertainty) and (economic or economy). See Alexopoulos and Cohen (2009) for a further discussion of this index and its relationship with indexes created using the words risk or risky instead of uncertain or uncertainty.

[11] USA Today and the Wall Street Journal are the two highest with a non-trivial share of their circulation attributable to hotels.

[12] The figures on current circulation are obtained through the Audit Bureau of Circulation's eCir database at http://abcas3.accessabc.com/ecirc/newsform.asp and are current as of September 30, 2008. The statistics on the number of unique visitors to the Times website is obtainable from The Nielsen Company.

[13] See also the evidence in Alexopoulos and Cohen (2009)

[14] "All the News that's fit to print" has been the New York Times motto since 1897.

The intuition behind our choice of indicator is straight foreword. Newspaper publishers have every incentive to report of issues of wide spread interest in a timely manner because that is how they attract readers and thus make money. As such, they are quick and through in their coverage of events that are likely to affect the economic wellbeing of their readers for the obvious reason that this reflects perfectly what their audience wants and needs. Unanticipated political turmoil, terrorist attacks, financial crisis, and so on, will cause the number of articles that deal with the economy and uncertainty to jump and will, therefore, provide an accurate account of the swings in anxiety felt by the general public. [15] It is because of this that we refer to our newspaper based index as the Main Street measure of uncertainty.

A few examples of the nature of articles associated with jumps in our index will illustrate why we believe it provides a sound indicator of uncertainty shocks. In mid August, 1971 President Nixon, in a surprise move, unilaterally introduced a 10 percent surcharge on imports and announced that the U.S. would cease to convert foreign-held dollars into gold. At the same time, he imposed a wage-price freeze. As our index indicates, the number of articles that satisfy our criteria jumped sharply from that time until the end of the year and as Eileen Shanahan (NYT, August 17, 1971) points out in President's Triple Ploy, everyone seemed unsure about the impact of these policy changes. As she put it, "If predicting the results of Mr. Nixon's move on gold is a job for a fortune-teller, predicting the outcome of the wage-price freeze may be a job for a psychiatrist."

[15] It is also likely that TV coverage of the events also increase during these turbulent economic times. See e.g., Doms and Morin (2004).

In another example, our uncertainty index shoots up in August 1990 in response to the Iraqi invasion of Kuwait. News stories raise questions about the quality of U.S. intelligence, the nature of the probable U.S. response, and the impact of all of this on an already faltering economy. As David Rosenbaum observes ("Deeper Economic Uncertainties Confront U.S. Policy Makers", NYT August 3, 1990), "For the economic policy makers in the Bush Administration, Congress and the Federal Reserve, Iraq's invasion of Kuwait creates a new storm in an already unsettled atmosphere." A budget impasse in October kept uncertainty high and in January 1991, uncertainty soared with the outbreak of war. As a final example, as our index indicates, 9/11 constituted a dramatic uncertainty shock. In an article published the day after the event, Louis Uchitelle ("A Tragedy Adds More Confusion To the Outlook For the U.S. Economy", NYT, September 12, 2001) commented, "The World Trade Center tragedy canceled all forecasts abut the American economy. And whatever happens next in the United States, in turn, will inevitably affect the global economic outlook." In short, then, it seems reasonable to argue that this index does capture broad-based uncertainty shocks.

The Comparison:

Given the high contemporaneous correlation between the two HP filtered series (0.47), it is likely that they capture many of the same events.[16] For comparative purposes we present, in Figure 2, the fluctuations in the measures. In Panel A, we graph the detrended log of both articles and Industrial Production, while in Panel B, we depict the HP filtered logs of the

[16] The smoothing parameter, λ, is set to 129,600.

volatility and industrial production indices. In both panels, we also shade in NBER identified recessions. They suggest that, on the whole, the two measures of uncertainty are countercyclical, that is swings in uncertainty move inversely with industrial production.[17] While correlation does not establish causality, this relationship does, at least, conform to our expectations.

That said, there are important differences in the behavior of the two series that merit attention. In mid 1971 while the newspaper index reveals a sharp spike in Main Street uncertainty linked to the international currency crisis, stock market volatility suggests that investors were only mildly perturbed by the event. On the other hand, the collapse of Franklin National in the fall of 1974 sent uncertainty shock waves through the canyons of Wall Street but had little effect on the sentiments of Main Street residents. In a similar vein, while Black Monday (October 1987) caused stock market volatility to rocket upwards, the impact on the newspaper index was much more muted. A series of shocks in the 1990s, including a deepening recession in 1990, a budgetary impasse in the U.S. and a currency crisis in Europe in 1992, as well as the start of the Asian financial crisis in October of 1997 stirred up uncertainty on Main Street but not on Wall Street. Some shocks, of course, were dramatic enough to send tremors through both – the assassination of President Kennedy, the attack on 9/11, and the current credit crunch. These comparisons – see Tables A1 and A2 in Appendix A for these and others – do suggest a pattern. The volatility index would often seem to reflect finance related shocks, the kind to mostly likely to pre-occupy Wall Street, while that based on newspaper articles appears more closely linked to broad based shocks, precisely the type to foster anxiety on Main Street.

[17] The contemporaneous correlation between detrended Industrial production and the detrended log(NYT) is -0.204 and the analogous correlation for detrended log(Vol) is -0.024.

Section 3.

In this section, we provide answers to two fundamental questions associated with post-war business cycles in the U.S. First, have uncertainty shocks been a major contributor to these fluctuations and, second, do investment and consumption react to the shocks as the conventional wisdom would have us believe? The motivation for the first is obvious; as for the second, there is in the literature a wide range of views about the effect of uncertainty shocks on consumption and investment. Our results should help us sort among them and shed some light as well on model selection. We proceed as follows in the remainder of this section. We review briefly our data and then report the results of a series of bi-variate and multi-variate vector-autoregressions in which we first focus on the impact of uncertainty shocks as measured by both the New York Times and the stock market volatility indexes on industrial production (IP) -our monthly measure of output- employment, unemployment, and labor productivity and then on consumption and investment.

The Data:

In addition to Bloom's (forthcoming) volatility measure and our monthly New York Times index, we gathered output, employment, price, interest rate, consumption and investment data from a number of sources. To facilitate a comparison with his results, we examine data for the period July 1962- November 2008 and detrend them using an HP filter with parameter λ=129,600. The Federal Reserve's FRED database is the source of the following numbers: the industrial production indexes (total, business equipment, consumption goods, durable goods and

non-durable goods), retail sales, the consumer price index (CPI: total goods), the federal funds rate, the monthly population, hours and employment. The Standard and Poor's index was downloaded from the Basic Economics Database (formerly known as Citibase) while the monthly personal consumption series (total, durables, non-durables and services) and the quarterly investment data (converted to a monthly frequency using the DISTR function in RATS) were drawn from the Bureau of Economic Analysis' website. Finally, similar to Carlino et al. (2001) and Horvath and Verbrugge (1996), we create two measures of monthly labor productivity. The first, output per worker, is defined as total industrial production divided by the total employment index, and, the second, output per hour, measured by total industrial production divided by total hours.

The Regressions:

I. Uncertainty, Output, Employment, and Productivity

A. The Bi-Variate Case

Our bi-variate VARs take the following form,

$$X_t = \alpha + \sum_{i=1}^{12} \mathrm{P}_i X_{t-i} + u_t$$

where α is a vector of monthly dummy variables (to remove monthly trends), X_t =[ln(NYT_t), ln(Y_t)]' or [ln($Volatility_t$), ln(Y_t)]' and Y_t is one of the following at time t: Industrial Production, Aggregate Employment, Manufacturing Employment, the unemployment rate, or a measure of

labor productivity.[18] To make the comparison with Bloom (forthcoming) as simple as possible, we also report the results of VARs with all variables are detrended using an HP filter and specified with 12 lags. We also use a Choleski decomposition to identify the uncertainty shocks and, as such, order our measures first in keeping with the assumption that these shocks affect the other variable contemporaneously.

Figure 3 reports the impulse responses of our variables to a one standard deviation uncertainty shock along with one standard deviation error bands. They show that an unanticipated increase in uncertainty leads to a drop in industrial production and employment, a rise in unemployment, and, in keeping with Bloom (forthcoming), a noticeable fall in productivity. A few features of the results merit special mention. First, it would seem that the low points of the various variables are reached a bit earlier for volatility than for article based shocks, although, in both, the bottom is reached within 12 to 15 months of the downturn. Second, a one standard deviation Main Street uncertainty shock appears to be associated with slightly greater declines in output, employment, and productivity than a Wall Street one and, third, recovery from the trough is moderately more rapid for the former than for the latter. In both cases, however, the recovery, when it begins, is dramatic and in both economic activity remains above trend for approximately one year.[19] Finally, the drop in productivity in response

[18] Bloom's (forthcoming) uses his actual volatility index in his sensitivity analysis. We opt to use the log of the volatility index. However, the differences in the results are minimal.

[19] Bloom (forthcoming) and Bloom, et al (2009) develop models that attempt to explain this overshoot. In essence, firms are thought to operate near their investment and employment thresholds so that negative

to these "second moment" shocks indicate that a substantial portion of productivity fluctuations may be linked to uncertainty shocks as opposed to the standard level technology shocks.

The variance decompositions presented in Table 2 indicate that uncertainty shocks have a powerful effect on output, employment, and productivity within a very short period of time. Specifically, at a twelve month horizon, close to 13 percent of the variance in industrial production, 21 percent in employment, 17 percent in the rate of unemployment, and 18 percent in output per person hour is attributable to the uncertainty captured by the New York Times index. The results, while less pronounced, are similar for the volatility index. More striking, however, are the differences in explanatory power of the two indicators. Innovations in the Main Street index, for example, at a three year (36 month) horizon, account for roughly a quarter of the variation in Industrial production, one third of the variance in employment, 28 percent in the unemployment rate and a little more than 20 percent in output per person hour. Over the same interval, the Wall Street indicator picks up 13 percent of the variance in industrial production, 16 percent in employment, just over 16 percent in the unemployment rate, and a mere 7.5 percent in output per person hour. In light of these results, it would seem safe to assume that the articles' based index provides a more comprehensive measure of these second moment shocks than does the volatility one.

B. The Multi-variate Case:

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uncertainty shocks lead initially to no response while positive shocks engender increases in investment and employment.

While the results of the bi-variate VARs are suggestive, it is reasonable to wonder if the results are sensitive to the inclusion of other shocks. To address this issue, we run a series of multi-variate VARs, in which we include the Ramey-Shapiro dates (to capture large fiscal shocks), the federal funds rate (to identify monetary policy shocks), the log of spot prices for oil (to account for oil shocks), and the Beaudry and Portier (2006) variable, log(S&P 500/CPI/POP), to capture 'news' shocks. Since we once again identify our shocks using a Choleski decomposition, the ordering of the variables is likely to matter. We place the uncertainty measures – either volatility or newspaper based – first because it accords with our belief that the other shocks respond to these instantly.[20] Subsequent ordering conforms, for the most part, with common practice. For example, in keeping with Christiano et al (1997) we introduce our quantitative variable (output, employment, or productivity) before the federal funds rate (FF), and order the price variables after it. This choice reflects the standard assumption that prices can respond to these shocks quickly but it takes time before quantities adjust. Finally, of the two remaining variables we place the 'news' shocks last, as do Beaudry and Poitier (2006), because they are presumed to pick up information on future productivity and should therefore affect variables like output, productivity and employment with a lag. Based on these considerations, we estimate the following VAR:

$X_t = \alpha + \sum_{i=0}^{12} RS_{t-i} + \sum_{i=1}^{12} \mathrm{P}_i X_{t-i} + u_t$ where α is again a vector of monthly dummy variables (included to remove seasonality), and RS is the exogenously determined Ramey-Shapiro dummy variable (and 12 lags) which takes on the value of one for the dates February 1965 (associated

[20] This ordering assumption is consistent with Bloom (forthcoming). Further it assumes that the other shocks in the system can only influence the uncertainty measures with a lag (if at all).

with the Vietnam War), December 1979 (USSR invasion of Afghanistan), September 2001 (Terrorist attack on pentagon and World Trade Center) and zero otherwise. X_t =[ln(NYT_t), ln(Y_t), FF, log(oil), log(S&P 500/CPI/POP)]' or [ln($Volatility_t$), ln(Y_t), FF, log(oil), log(S&P 500/CPI/POP)]' and Y_t is again one of IP_t, Aggregate $Employment_t$, Manufacturing $Employment_t$, the time t unemployment rate, output per worker or output per labor hour. The variance decompositions and impulse response functions associated with these systems are presented in Table 3 and Figure 4.[21]

The impulse responses for the multi-variate case – with the inclusion of fiscal, monetary, oil price, and news shocks – are remarkably similar to those for the bi-variate one. A few differences, however, are worth noting. First, the low point for the quantitative variables comes earlier in the volatility driven multi-variate case than it does in the bi-variate one. Second, both sets of impulse-responses indicate a bottom within 6 to 15 months followed by a boom and overshoot for approximately one year. If anything, the recovery, especially for the articles' based index, is more rapid for the multi-variate than for the bi-variate case and the overshoot in industrial production and employment is greater.

As indicated in Table 3, although the explanatory power of uncertainty declines with the inclusion of additional shocks, it still accounts for a non-trivial amount of the variation, roughly comparable, in fact, with monetary policy shocks. Thus, at an 18 month horizon, uncertainty

[21] Appendix B demonstrates that the results are not sensitive to replacing the number of actual articles with an index normalized by the number of other articles printed in the New York Times, or adding the HP filtered log of the other articles to the VAR.

picks up roughly 14 percent of the variation in industrial production, 24 percent in aggregate employment, 18 percent of the unemployment rate and about 7 percent of output per worker. Moreover, the data show that the Main Street index continues to outperform the Wall Street one for all variables. The timing of the impact also changes. For employment and output, the amount of the variation attributable to uncertainty reaches a maximum at an 18 month horizon compared with between 24 and 36 months in the bi-variate case.

Figure 5 helps put the negative consequences of uncertainty shocks in a different and perhaps more telling context. Here we look at the reactions of output and employment to an unanticipated monetary policy shock that increases the Federal Funds Rate by 1 percent, and an uncertainty shock that increases one or the other of our two measures by 50 percent.[22] The results are striking. In response to the uncertainty shock, output and employment touch bottom quickly and return to pre-shock levels roughly at the same time that they hit the lowest point following a monetary policy shock. Moreover, the magnitude suggests that this size of this uncertainty shock exacts more damage on the economy than the monetary policy one. The variance decompositions tell a similar tale for the short run impact. Thus, by month 12, the articles based shock picks up 9.6 percent of the variance in industrial production, the federal funds rate captures only 4.4 percent. Although the difference is less dramatic for volatility measured uncertainty, these shocks still account for 7.9 percent in the variance of industrial production by month 12, as apposed to 4.2 percent for the federal funds rate. The numbers are, if anything, more extreme for employment. At a one year horizon, 20.5 percent of the variance is

[22] As Figure 1 shows, many of the increases in uncertainty captured by the indexes are in this range – which is significantly less than the increases seen in the last few months of 2008 (See also Table 1).

attributable to our uncertainty index (and 14 percent to the volatility one), verses a mere 2.5 percent for the federal funds rate.

C. The Tri-Variate Case: Main Street versus Wall Street

The greater explanatory power of the Main Street index raises an interesting question about the two measures. Does the newspaper index capture all the information contained in the volatility indicator and then some or are the two just picking up different aspects of aggregate uncertainty? To answer this question, we ran a series of tri-variate VARs in which we include in addition to output, employment, the unemployment rate, and productivity both measures of uncertainty, first ordering volatility before the newspapers and then giving the latter priority over the former. In other words, we first assume X_t =[ln(Volatility),ln(NYT_t), ln(Y_t)]' where again Y_t is one of IP_t, Aggregate $Employment_t$, Manufacturing $Employment_t$, the time t unemployment rate, and the two productivity measures and then reverse the ordering of the first two variables in the second case. This allows us to determine if the additional uncertainty picked up by our NYT index (the part not captured by the volatility measure) has a significant impact on cyclicality. The variance decompositions are reported in Table 4 and the impulse responses in Figures 6 and 7.

In the case of volatility first, the impulse responses show patterns similar to those we observed in the bi-variate and multi-variate regressions, a bottom reached within 6-15 months followed by a sharp recovery and an overshoot. Newspaper based uncertainty continues to affect fluctuations in output, employment, and productivity, an indication that Main Street anxiety plays an important role. This is confirmed by the variance decompositions in which the addition

of the New York Times index expands significantly the explanatory power of uncertainty, in some cases (employment and output per hour) in excess of that attributable to volatility.

The same pattern emerges with the newspaper index ordered first. However, the depth of the contraction attributable to volatility is now diminished. Without exaggerating the importance of this result, it does seem to suggest that newspaper based shocks capture much of what is picked up by volatility – plus much that the latter misses. Again, the variance decompositions reinforce this impression. As can be seen in Panel B of Table 4, the variance attributable to stock market volatility drops dramatically across all variables when the New York Times index takes precedence in the ordering, never adding more than 9 percent at a five year horizon and in most cases much less. This contrasts sharply with the previous case where, aside from output per worker, the newspaper index consistently added 11 percent or more. In short, there is every reason to believe that the New York Times index captures important broad-based uncertainty shocks.

II. Consumption and investment

A. Background

In addition to the issues associated with the link between uncertainty shocks and fluctuations in output, employment, and productivity, there is a large literature focused on the relationship between uncertainty and consumption and investment. The question, of course, is what impact, if any, do swings in uncertainty have on these principal components of aggregate demand? Once again, we employ VARs with short run restrictions to provide an answer.

A very brief review of the literature is necessary to shed light on our choice of variables. Romer (1990) argues that the jump in uncertainty caused by the stock market crash in October 1929 had a major negative effect on consumption expenditures, especially of consumer durables, which in turn contributed significantly to the economic collapse that followed. Her reasoning was simple but compelling. Even though most individuals were not shareholders at the time, they still looked to the stock market as an indicator of the state of the economy. The Crash was a terrifying event, difficult to interpret perhaps, but clearly a threat to house and home. Since consumer durables constituted major, indivisible outlays, households, faced with heightened uncertainty about income and employment, would have to consider seriously postponing these purchases until the future was less opaque. If they erred on the caution, they merely suffered a temporary reduction in their utility. If their caution turned out to be well-founded, the money saved provided some shelter from the storm. In a subsequent article, Greasley, Oxley, and Madsen (2001) argued, using similar measures, that the rise in uncertainty following the crash had an equally devastating impact on the demand for services for much the same reasons. Although our focus in this article is on the post-war years, our results do shed light on the overall relationship between Main Street and Wall Street uncertainty shocks on both aggregate consumption and on durable and non-durable expenditures.

There is much less agreement in the literature about the relationship between uncertainty shocks and investment. Abel (1983) and Caballero (1991) argue, for example, that a rise in uncertainty is likely to lead to an increase in investment while Bernanke (1983), Greasley and Madsen (2006), Bloom et al (2007) and Bloom (forthcoming), among others, make exactly the opposite the case. The central issue in the controversy is the trade-off between lost profits

caused by postponed investments (influenced by the structure of industry, the pace of technical change, and adjustment costs) versus the potential gains associated with caution in the face of "unknown unknowns". Again, our regression results help speak to this controversy and, implicitly, may help us discriminate between competing models.

B. The Data and the Regressions

To examine the responses of consumption and investment goods to uncertainty shocks, we use two groups of numbers, one based on the production of these types of goods, the other on business and personal expenditures. The impulse responses for retail sales and for the production of business equipment, all consumer goods, as well as durable and non-durable goods are presented in Figure 8. In Figure 9 responses for consumer expenditures (total and by major subgroup) are shown, and in Figure 10 those for investment (total and by type) are depicted.

A comparison of these figures shows that the responses of the variables are similar regardless of whether we examine production indices or measures of expenditures. Furthermore, the magnitude of the drops in either consumption or investment in response to a positive uncertainty shock is roughly the same whichever of the two measures we employ. Moreover, the patterns resemble those observed for output, employment, and productivity bottoming between months 6 and 15, springing rapidly back to trend, and, in most cases, overshooting for a year or two.

There are, however, some notable differences between the impacts of the two uncertainty measures. Main Street shocks, it seems, drive down the production of non-durables less than

Wall Street ones do. On the other hand, they push down the production of durables, overall consumption, and business equipment further than their volatility counterpart. The variance decompositions recorded in Table 5 tell a similar tale. Both measures of uncertainty, with one marked exception, account for sizeable shares of the variance. The exception is the surprisingly minor affect of the volatility index on business equipment output.

Figure 9 suggests that expenditures on services declines least following an uncertainty shock, while purchases of durable goods responses most (regardless of the measure used). Moreover, even though both sets of graphs display the overshoot, recovery occurs faster following a Main Street shock.

Figure 10 reports the analogous responses for investment and its major subgroups. We find that the overall decrease in investment following either of our two uncertainty shocks is similar in size although the decline does appear to be steeper in the case of the volatility shock. Further, a comparison of the subgroups' responses highlights some interesting differences. In particular, a newspaper measured uncertainty shock seems to have the largest impact on non-residential investment and on the purchase of business equipment and software, whereas that of a volatility shock is greatest on residential investment.

The variance decompositions reported in Table 6 reinforce the importance of uncertainty in explaining short run fluctuations in consumption and investment although, once again, the two measures reveal slightly divergent results. For example, our New York Times index accounts by year five for over one third of the variation in non-residential investment, 29 percent of that in

business and software, and nearly 20 percent of non-durable consumption. On the other hand, the volatility measure has its greatest pull on personal consumption (20 percent), durable (24 percent) and non-durable (19.9 percent) expenditures and gross investment (28.9 percent).

We can draw the following conclusion from these results. First, in keeping with the views of Bernanke (1983), Bloom et al (2007), Bloom (forthcoming) and others, positive uncertainty shocks have a negative impact on capital expenditures. Moreover, investment spending is highly attuned to broad-based measures of uncertainty which is at least consistent with the idea that firms in making their investment decisions worry about those infamous "unknown unknowns". Second, it would seem that the use of stock market volatility to measure uncertainty as Romer (1990) and others do is less questionable than some may believe. Third, our results leave little doubt that uncertainty shocks do have a powerful affect on consumption and investment decisions.

In Figures 11-13 and Tables 7 and 8, we report the results of our multi-variate VARs with the ordering conforming to that described earlier. In this case, we again run the regressions separately for each of the two uncertainty measures. These findings can be reviewed relatively briefly since they show patterns similar to the earlier ones. Again, however, a few features deserve special mention. With the inclusion of other shocks, recovery starts earlier and the decline linked to uncertainty shocks is more modest. Most striking is the contrasting fortune of the volatility measure (see Tables 5 and 6 verses 7 and 8). While both of the indexes loose some of their explanatory power, the New York Time index continues to account for a substantial share of the variance in most variables (often between 10-20 percent). The same cannot be said

for the volatility measure, which by year 5 picks up less than 10 percent of the variance with only two exceptions, gross and non-residential investment. We can, with some confidence infer from these results that our newspaper based index provides, at the very least, a compelling addition to the Macroeconomists' toolkit.

Conclusions:

In this paper we attempt to answer the question, are uncertainty shocks an important source of cyclical fluctuations? We find evidence they are – especially if they represent changes in uncertainty felt by both individuals on Main Street and Wall Street. To determine the impact of these shocks we estimate a series of VARs with two measures of uncertainty: the standard measure – stock market volatility – and a new measure we create using the number of New York Times' articles that contain the words uncertain or uncertainty along with economic or economy. We find evidence that an unanticipated increase in uncertainty, regardless of the measure, can result in sharp, short lived, recessions. Industrial production falls, as does employment, consumption, productivity and investment, and unemployment rises. The responses to these shocks are rapid and the recovery time relatively short. Overall, the patterns suggest a role for models of the kind presented in Bloom (forthcoming) and Bloom et al. (2009), and the responses of investment can help discriminate between competing theories of how uncertainty changes investment behavior.

Even though the impulse responses generated using the different measures are similar, our results show that our new newspaper based index outperforms the volatility index in terms of

its explanatory power. Indeed our findings based on New York Times index suggests that uncertainty shocks should be added to the list of monetary policy shocks, technology shocks, oil price shocks and news shocks as a significant contributor to short run business cycle fluctuations. As such, future research should: (1) focus on indentifying which types of uncertainty shocks are most damaging to the economy, and (2) create models that explicitly capture these shocks.

Our findings also indirectly answer King and Rebelo's (1999) question concerning the role of productivity shocks in creating business cycles. Specifically, they ask "if these shocks are large and important, why can't we read about them in the Wall Street Journal?" Indeed our results suggest that we are, in fact, reading about them in the Journal, the New York Times and in other newspapers. It is simply that the large and important shocks we are reading about are events that cause increased levels of uncertainty, which, in turn, decreases productivity, output and employment. Accordingly, is may be necessary to reexamine what we think of as productivity shocks – especially negative ones.

Finally, policy makers should be mindful of our results. They suggest that any policies, presentations of policies, or delays in action that increase the level of uncertainty in the economy can be very damaging. Unfortunately, we have recently seen an example of this in October when Congress failed to pass the expected stimulus/bailout plan. Our measures of uncertainty rapidly shot up after the event and, consistent with the results presented in this paper, the most recent statistics show the economy slipping deeper into recession.

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Appendix A: Timing

Here we report dates identified by Bloom (forthcoming) as major stock market volatility dates (Table A1), and some additional dates that are picked up by our indicators (Table A2). These tables help demonstrate the types of events – both large and small – that influence our indicators. Moreover, we have included a few dates in Table A2 that illustrate how the newspaper index may be better able to identify the timing of increased uncertainty linked to events such as the second Gulf War and the Russian Currency Crisis.

Table A1: Bloom's Major Stock-Market Volatility Shocks- initial volatility dates

Bloom's Dates	
October 1962	Cuban Missile Crisis
November 1963	Assassination of JFK
August 1966	Vietnam build-up
May 1970	Cambodia and Kent State
December 1973	OPEC I, Arab-Israeli War
September 1974	Franklin National
November 1978	OPEC II
March 1980	Afghanistan, Iran Hostages
August 1982	Monetary cycle turning point
October 1987	Black Monday
September 1990	Gulf War I
November 1997	Asian Crisis
September 1998	Russian, LTCM Default
September 2001	9/11 Terrorist Attack
July 2002	Worldcom and Enron
February 2003	Gulf War II
August 2007	Credit crunch

Table A2: Examples of dates captured by New York Time Index in addition to those above

Date	Topics Covered by Articles
January 1970	Business cycle date
November 1970	Election & oil issue
August 1971	Issues of currency (going off gold standard) and exchange rates
November 1973	middle east war & oil
September 1975	News New York City may default on debt, oil issues (price controls to end) & NYC crisis causes strikes
November 1976	Bad economic news, more fiscal problems announced in NYC & problems with trading partners - in Canada Quebec Separatists win election and Mexico suspends its currency
October 1977	Bad economic reports released
August 1981	Recession begins
February 1990	Talk of German reunification & problems in Japan
August 1990	News of weak economy
August 1992	issues of political uncertainty and drop in Dollar
September 1992	Political issues (Bush Campaign & upcoming election) and economic problems in Europe (e.g. European unity)
October 1992	Currency crisis in Europe
January 1996	Federal government shutdown because of budgetary impasse
October 1997	Reporting on Asian crisis starts
May 1998	Problems in Russia emerging and issues emerge in Latin American linked to the Asian Crisis (their stock markets tumble)
August 1998**	July 20, 1998 IMF approves an emergency aid package (first disbursement to be $4.8 billion), August 13, 1998: Russian stock, bond, and currency markets weaken as a result of investor fears of devaluation, August 17, 1998 Russian government devalues the ruble, defaults on domestic debt, and declares a moratorium on payment to foreign creditors
November 2000	Bush vs. Gore election issues & political unrest in Asian countries
September 2001	9/11
July 2002	Worldcom Collapses
October 2002	debate about war with Iraq & bad economic news (poor profits)
January 2003**	Announcement Iraq isn't in compliance with UN resolutions
February 2003**	Colin Powell addresses UN
March 2003**	Gulf war 2 starts
October 2004	Election & Disappointing profit reports
September 2005	Katrina & Rita Hurricanes hit US, Impact on oil prices & problems with Iran

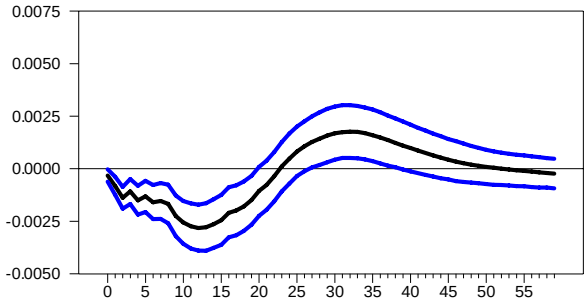
***slight differences in dates from those identified in Table A1

Appendix B: Some Sensitivity Results

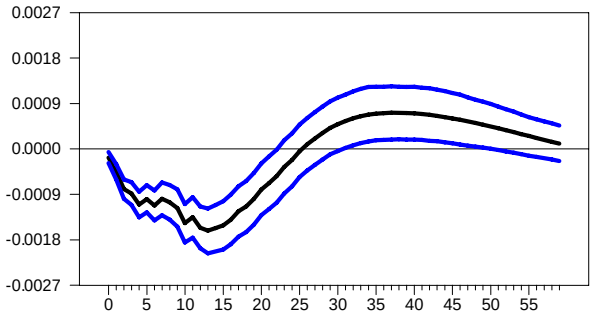
On might wonder how our findings would change if we were to utilize a newspaper measure that is normalized by the number of articles not on issues of uncertainty and the economy, or include a measure of these other articles in the regressions. To address these issues we present here a selected set of results to demonstrate that our findings are robust to both of these changes. Here we examine two sets of multi-variate VARs for industrial production and employment (i.e., the VARs with the monetary, fiscal, oil and news shocks variables included). The first uses the normalized index. The second includes the number of other articles before the uncertainty measure to insure that the shocks affecting all newspaper articles are already controlled for when we examine the impact of uncertainty shocks. Of course, given that the other articles may also increase during uncertain times because: (1) they include stories that talk about uncertainty or the economy (but not both together) or (2) they talk about the times, but use other terms to describe the uncertainty (like risky), the results based on either the normalized index or on a system that includes the 'other articles' ordered before the uncertainty index may underestimate the true impact of uncertainty shocks. However, a comparison of the impulse responses in shown in Figure 3 with those depicted below show the differences in the results are negligible. Moreover, the variance decomposition results reported below are very similar to those presented in Table 3.

Impulse Responses for VAR with normalized number of articles used:

Industrial Production

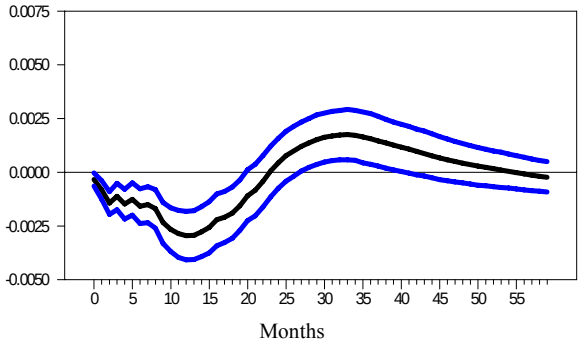


Employment

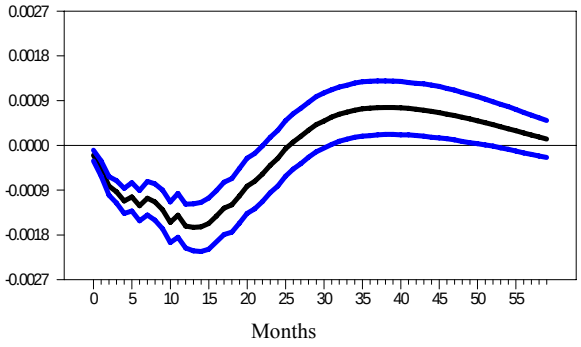


Impulse Responses for VAR with the detrended log of the other articles included and ordered before the uncertainty index

Industrial Production



Employment



Notes: Each panel depicts the variable's response to a one standard deviation shock and includes one standard deviation error bands.

Variance Decompositions: Multi-variate VARS for sensitivity analysis

horizon (in months)	Industrial Production (normalized Index)	Aggregate Employment (normalized index)	Industrial Production (other articles included)	Aggregate Employment (other articles included)
1	0.25	0.55	0.29	0.74
6	3.01	10.67	3.15	11.40
12	7.26	16.91	7.95	18.45
18	10.34	22.42	11.35	23.51
24	9.44	20.30	10.36	21.22
36	9.67	16.73	10.59	17.81
48	9.90	17.28	10.91	18.51
60	9.66	17.36	10.64	18.59

Table 1

Newspaper	**Average Daily Number of articles with reference to uncertainty and the economy**					**Average Weekday Circulation**
	2007	2008	October 2008	November 2008	December 2008	Sept. 30, 2008
New York Times	1.09	2.36	4.13	3.87	2.77	1,000,665
L.A. Times	0.65	1.10	2	1.27	1.48	739,147
U.S.A Today	0.23	0.48	0.68	0.6	0.61	2,293,310
Wall Street Journal	1.98	3.39	5.29	3.43	2.74	2,011,999
Washington Post	0.76	1.59	3.48	1.9	1.65	622,714
Chicago Tribune	0.56	1.06	1.32	1.6	1.03	516,032
Circulation weighted Average	0.95	1.76	2.88	2.1	1.72	n/a

Table 2: Variance Decomposition for Bi-variate VARs

Panel A: New York Times Index

horizon (in months)	Industrial Production	Manufacturing Employment	Aggregate Employment	Unemployment rate	Output per worker	Output per hour
1	0.22	0.14	0.52	0.59	0.17	0.11
6	4.68	5.00	10.53	7.88	3.13	2.32
12	12.87	15.30	20.99	17.31	9.39	8.40
18	21.57	27.31	29.39	25.71	16.09	18.33
24	24.38	32.68	32.87	28.90	17.62	21.24
36	23.78	31.95	33.39	28.37	17.57	21.30
48	25.01	33.42	33.52	29.38	18.17	22.08
60	24.95	33.58	33.94	29.51	18.16	22.09

Panel B: Volatility Measure

horizon (in months)	Industrial Production	Manufacturing Employment	Aggregate Employment	Unemployment rate	Output per worker	Output per hour
1	0.75	0.01	0.00	0.41	0.68	1.37
6	2.80	3.91	2.38	5.07	2.88	1.11
12	7.27	8.47	8.42	10.49	7.10	2.54
18	11.75	12.19	13.16	14.51	11.72	5.99
24	13.34	13.61	15.76	16.59	12.89	7.60
36	12.81	13.30	16.48	16.09	12.47	7.48
48	13.62	13.92	16.51	16.47	13.06	7.82
60	13.57	13.94	16.71	16.60	13.01	7.81

Table 3: Variance Decompositions for Multi-variate Case

Panel A: New York Times Index

Horizon (in months)	Industrial Production	Manufacturing Employment	Aggregate Employment	Unemployment rate	Output per worker	Output per hour
1	0.29	0.13	0.57	0.72	0.21	0.05
6	3.92	3.93	11.78	7.08	1.96	0.52
12	9.57	12.00	20.46	13.13	5.00	2.84
18	13.99	21.07	24.32	18.01	6.88	6.24
24	12.82	22.05	21.48	16.30	6.11	6.09
36	13.44	19.81	18.16	15.09	9.59	9.59
48	14.68	21.69	19.65	16.70	10.40	10.89
60	14.39	21.56	19.81	16.44	10.31	10.88

Panel B: Volatility Measure

Horizon (in months)	Industrial Production	Manufacturing Employment	Aggregate Employment	Unemployment rate	output per worker	Ouput per labor hour
1	0.51	0.00	0.03	1.04	0.48	0.82
6	4.08	5.41	5.19	7.77	3.42	1.76
12	7.89	10.29	14.03	12.83	5.41	3.08
18	7.64	11.29	15.35	12.81	4.66	3.19
24	6.50	10.11	12.98	10.78	4.65	3.14
36	6.34	8.67	9.96	8.58	5.38	4.47
48	6.37	8.58	10.08	8.59	5.33	4.39
60	6.25	8.46	10.18	8.43	5.25	4.32

Table 4: Variance Decompositions – Tri-variate case

Panel A: Ordering Volatility before Article Index

horizon (in months)	Industrial Production		Manufacturing Employment		Aggregate Employment		Unemployment rate		Output per worker		Output per hour	
	ln(Vol)	ln(NYT)	ln(Vol)	ln(NYT)	ln(Vol)	ln(NYT)	Ln(Vol)	ln(NYT)	ln(Vol)	ln(NYT)	ln(Vol)	ln(NYT)
1	0.70	0.37	0.00	0.12	0.02	0.66	0.44	0.26	0.66	0.27	1.34	0.41
6	3.15	1.46	4.83	1.92	2.80	6.88	5.66	3.93	3.26	0.61	1.40	1.45
12	8.06	5.78	10.46	8.97	9.37	11.95	11.55	9.35	7.86	3.42	3.41	5.81
18	12.68	10.35	14.12	17.89	13.77	16.72	15.50	14.23	12.68	6.12	7.37	11.84
24	14.52	11.52	15.66	21.45	16.12	18.34	17.65	15.57	14.13	6.46	9.50	12.71
36	14.12	11.30	15.33	21.04	16.64	18.52	17.27	15.41	13.76	6.71	9.49	13.15
48	15.05	11.86	16.00	21.93	16.81	18.56	17.72	15.99	14.44	6.97	9.93	13.58
60	15.03	11.83	16.03	22.00	17.09	18.70	17.86	16.03	14.40	6.99	9.94	13.61

Panel B: Ordering Article Index Before Volatility

horizon (in months)	Industrial Production		Manufacturing Employment		Aggregate Employment		Unemployment rate		Output per worker		Output per hour	
	ln(NYT)	ln(Vol)	ln(NYT)	ln(Vol)	ln(NYT)	ln(Vol)	ln(NYT)	ln(Vol)	ln(NYT)	ln(Vol)	ln(NYT)	ln(Vol)
1	0.12	0.95	0.10	0.02	0.67	0.01	0.47	0.24	0.07	0.86	0.07	1.68
6	2.49	2.13	3.81	2.94	8.63	1.05	6.64	2.95	1.34	2.52	1.70	1.16
12	9.47	4.36	14.39	5.04	17.36	3.95	15.25	5.65	6.31	4.97	7.63	1.58
18	16.64	6.39	26.27	5.75	24.73	5.77	22.52	7.21	11.26	7.54	16.30	2.90
24	18.68	7.36	31.01	6.10	27.52	6.93	24.88	8.34	12.10	8.49	18.08	4.12
36	18.28	7.14	30.42	5.96	27.92	7.24	24.50	8.18	12.27	8.21	18.31	4.33
48	19.28	7.63	31.74	6.20	28.04	7.33	25.36	8.35	12.79	8.62	18.98	4.53
60	19.23	7.62	31.83	6.20	28.31	7.48	25.45	8.44	12.80	8.59	18.99	4.55

Note: For each case, the numbers in columns labeled ln(NYT), and ln(Vol) give the percent of the variable's forecast error variance attributable to the NYT index and Volatility measure respectively.

Table 5: Variance Decomposition Bi-variate Case Production Measures and Retail Sales

Panel A: New York Times Index

horizon (in months)	I.P. Business Equipment	I.P Consumption Goods	I.P. Non-Durables Goods	I.P. Durables Goods	Retail Sales
1	0.70	0.13	0.41	0.01	1.24
6	4.89	4.41	7.35	1.61	6.22
12	14.11	10.99	14.42	7.38	15.50
18	22.38	15.91	17.53	16.54	20.45
24	26.08	16.99	17.88	18.64	21.72
36	25.56	16.97	18.02	18.82	21.67
48	26.58	17.26	18.15	19.31	22.22
60	26.97	17.27	18.16	19.32	22.23

Panel B: Volatility measure

horizon (in months)	I.P. Business Equipment	I.P Consumption Goods	I.P. Non-Durables Goods	I.P. Durables Goods	Retail Sales
1	0.06	0.03	0.02	0.01	0.88
6	0.80	7.97	9.54	2.90	7.91
12	3.49	15.50	18.44	6.11	14.02
18	6.75	21.99	23.13	14.29	22.15
24	9.04	23.72	23.79	17.65	25.64
36	9.06	23.35	23.74	17.81	24.87
48	9.33	23.82	24.08	18.28	25.79
60	9.75	23.83	24.07	18.29	26.08

Table 6: Variance Decompositions for Bi-variate Cases

Panel A: New York Times Index

horizon (in months)	Personal Consumption Expenditures	Expenditures on Durables	Expenditures on Non-Durables	Expenditures on Services	Gross Investment	Non-Residential Investment	Investment in Business Equipment & Software	Residential Investment
1	0.74	0.73	0.71	0.53	0.68	0.19	0.45	0.12
6	3.25	2.86	5.95	3.62	4.80	2.95	3.35	1.22
12	9.06	8.74	14.19	10.43	11.18	14.54	14.36	1.81
18	12.82	13.07	18.63	14.02	17.46	26.94	23.69	1.82
24	14.18	14.39	19.16	15.32	18.48	32.79	27.80	3.05
36	14.06	14.45	19.33	15.29	18.65	32.64	27.77	4.96
48	14.50	14.55	19.89	15.55	18.74	33.80	28.54	4.94
60	14.54	14.57	19.89	15.57	18.75	34.20	28.87	4.99

Panel B: Volatility measure

horizon (in months)	Personal Consumption Expenditures	Expenditures on Durables	Expenditures on Non-Durables	Expenditures on Services	Gross Investment	Non-Residential Investment	Investment in Business Equipment & Software	Residential Investment
1	0.96	0.61	0.90	0.83	0.77	0.23	0.21	0.31
6	7.43	6.94	5.71	4.36	9.69	2.18	2.17	4.80
12	10.13	13.90	8.14	5.36	23.08	7.22	7.66	6.79
18	16.24	20.73	15.97	8.24	27.89	11.18	12.19	7.55
24	19.85	23.49	19.35	10.31	28.64	13.39	14.82	7.53
36	19.82	23.68	18.53	10.85	28.64	13.20	14.86	7.70
48	20.03	23.85	19.85	10.82	28.94	13.66	15.18	7.76
60	20.59	24.00	19.94	10.95	28.93	13.84	15.52	7.77

Table 7: Variance Decompositions for Multi-variate Cases

Panel A: New York Times Index

horizon (in months)	I.P. Business Equipment	I.P Consumption Goods	I.P. Non-Durables Goods	I.P. Durables Goods	Retail Sales
1	0.64	0.15	0.43	0.00	1.41
6	2.78	3.46	7.51	0.11	4.51
12	8.33	6.44	10.19	2.47	14.11
18	13.34	6.95	8.66	6.32	16.33
24	14.88	6.58	9.02	6.16	15.19
36	14.21	10.63	14.03	8.78	17.50
48	15.40	11.36	14.49	9.34	18.27
60	15.30	11.24	14.43	9.39	18.24

Panel B: Volatility Measure

horizon (in months)	I.P. Business Equipment	I.P Consumption Goods	I.P. Non-Durables Goods	I.P. Durables Goods	Retail Sales
1	0.01	0.04	0.04	0.00	0.89
6	1.54	7.10	8.14	2.99	5.94
12	4.94	8.79	9.85	4.37	8.37
18	5.95	7.47	8.09	6.66	9.64
24	5.65	6.93	8.05	6.24	8.80
36	5.47	7.71	8.63	6.49	7.81
48	5.57	7.99	8.61	6.74	8.26
60	5.49	7.84	8.52	6.66	8.10

Table 8: Variance Decompositions for Multi-variate Cases

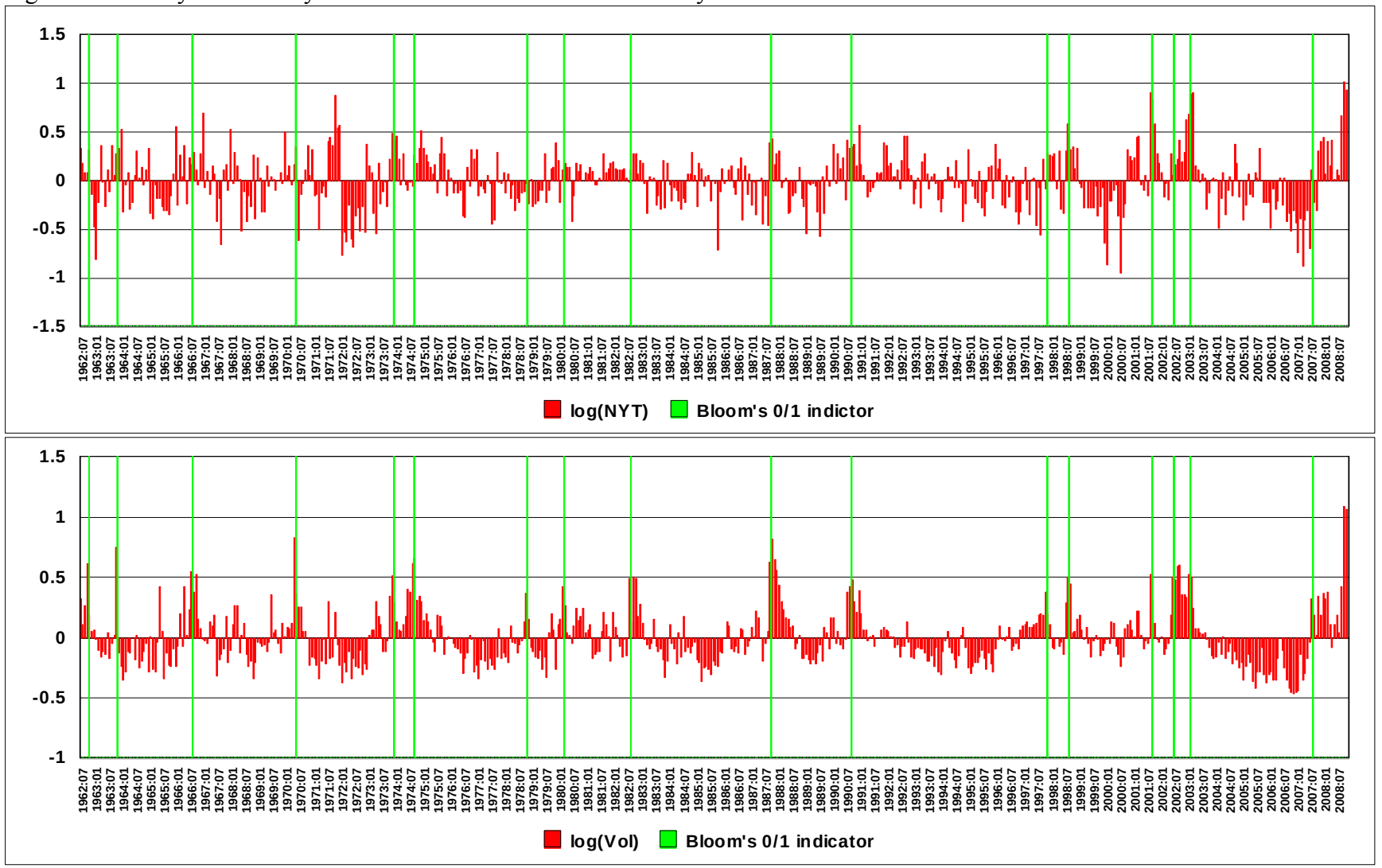
Panel A: New York Times Index

horizon (in months)	Personal Consumption Expenditures	Expenditures on Durables	Expenditures on Non-Durables	Expenditures on Services	Gross Investment	Non-Residential Investment	Investment in Business Equipment & Software	Residential Investment
1	1.04	1.39	0.48	0.38	0.39	0.15	0.28	0.09
6	2.62	2.13	4.71	2.25	3.48	1.14	1.00	0.47
12	9.39	5.96	13.13	8.17	5.92	9.43	8.45	1.34
18	10.57	6.63	14.78	8.99	8.91	18.17	14.59	1.73
24	9.58	6.69	14.00	8.58	7.50	19.50	13.99	4.94
36	12.04	10.94	15.64	10.70	10.58	17.54	12.71	8.57
48	13.33	11.88	16.07	11.89	11.13	18.48	13.69	8.09
60	13.23	11.93	16.08	11.81	10.81	18.21	13.45	8.16

Panel B: Volatility measure

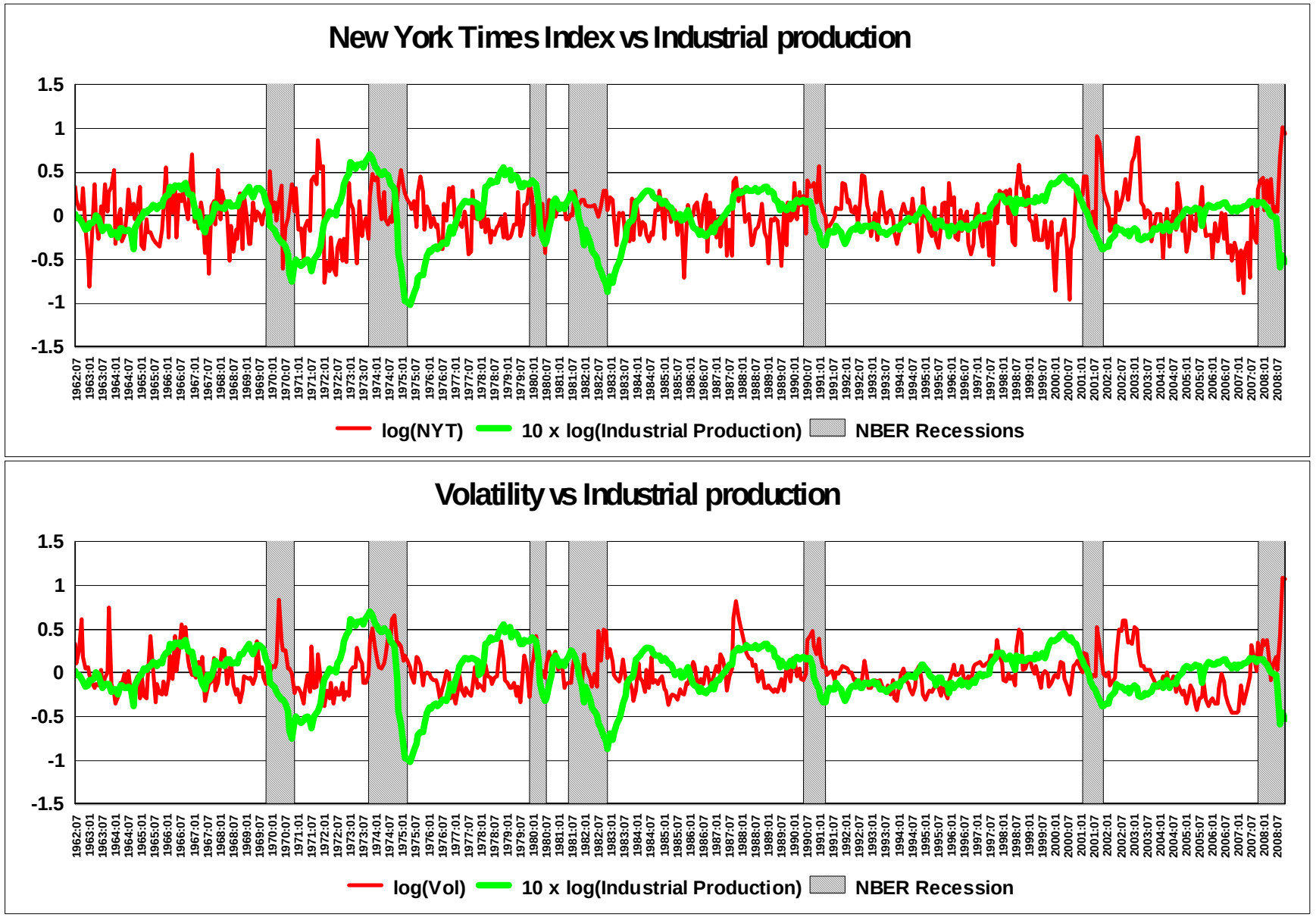
horizon (in months)	Personal Consumption Expenditures	Expenditures on Durables	Expenditures on Non-Durables	Expenditures on Services	Gross Investment	Non-Residential Investment	Investment in Business Equipment & Software	Residential Investment
1	1.31	0.60	1.54	1.42	0.97	0.37	0.41	0.16
6	5.70	3.66	6.21	3.85	11.28	3.93	3.59	3.67
12	6.21	5.23	7.44	4.11	19.60	11.36	9.92	3.60
18	6.62	4.75	10.45	4.12	16.39	13.46	11.52	3.28
24	5.92	4.33	10.39	3.86	15.06	12.57	10.21	3.63
36	5.45	5.09	9.09	4.12	14.43	11.40	8.84	3.47
48	6.20	5.67	9.73	4.29	14.03	11.18	8.76	3.28
60	6.17	5.59	9.56	4.25	13.62	10.95	8.57	3.24

Figure 1. Monthly Uncertainty Measures vs Bloom's 0/1 Uncertainty Indicator



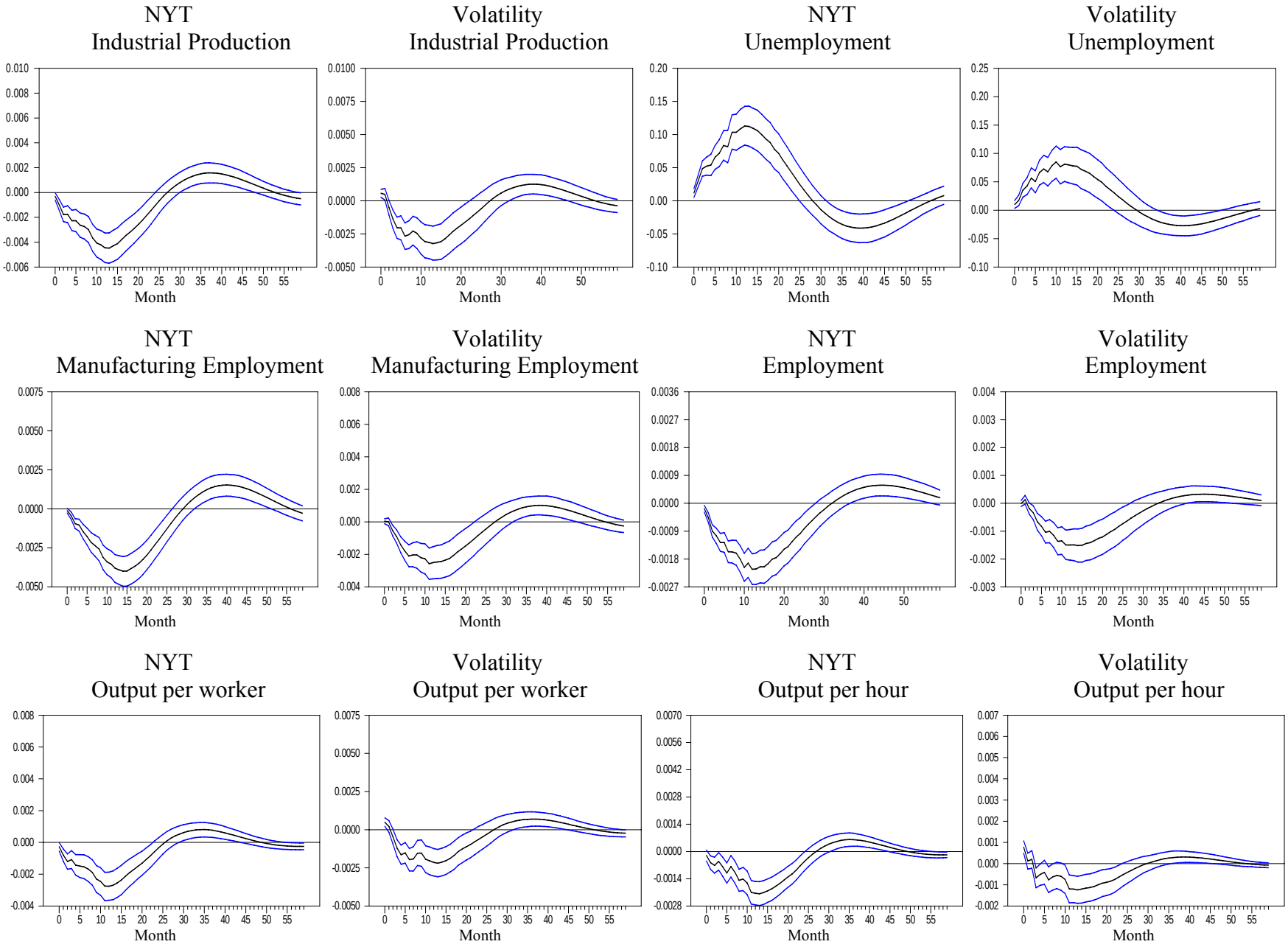
Notes: Bloom's 0/1 indicator refers to the measure he creates based on the S&P volatility to identify major uncertainty shocks. The log(Vol) and log(NYT) are HP filtered with smoothing parameter lambda=129600.

Figure 2. Cyclicality of indicators



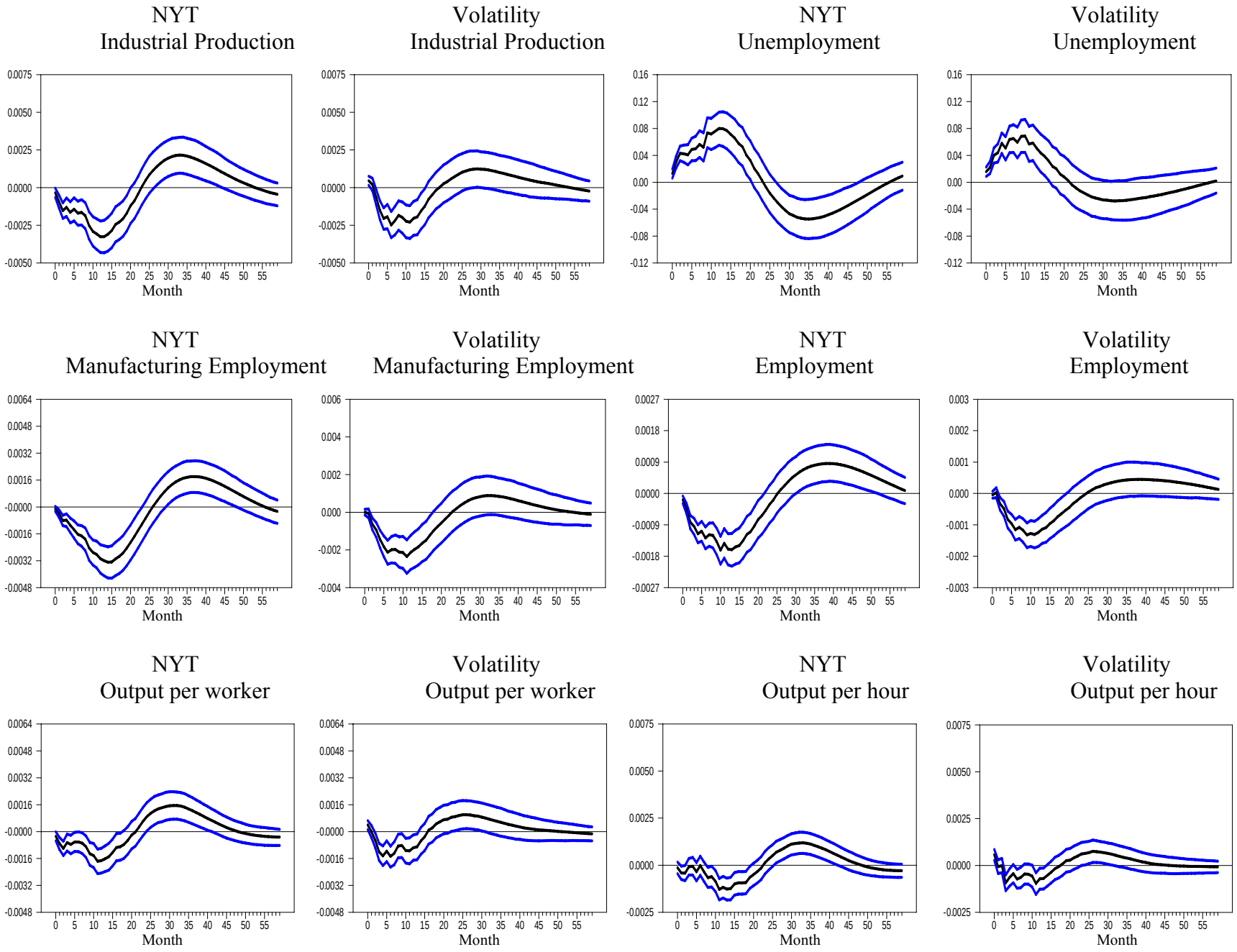
Notes: All variables are HP-filtered with smoothing parameter lamba = 129600.

Figure 3. Response of Variables to Uncertainty Shocks – Bivariate Case



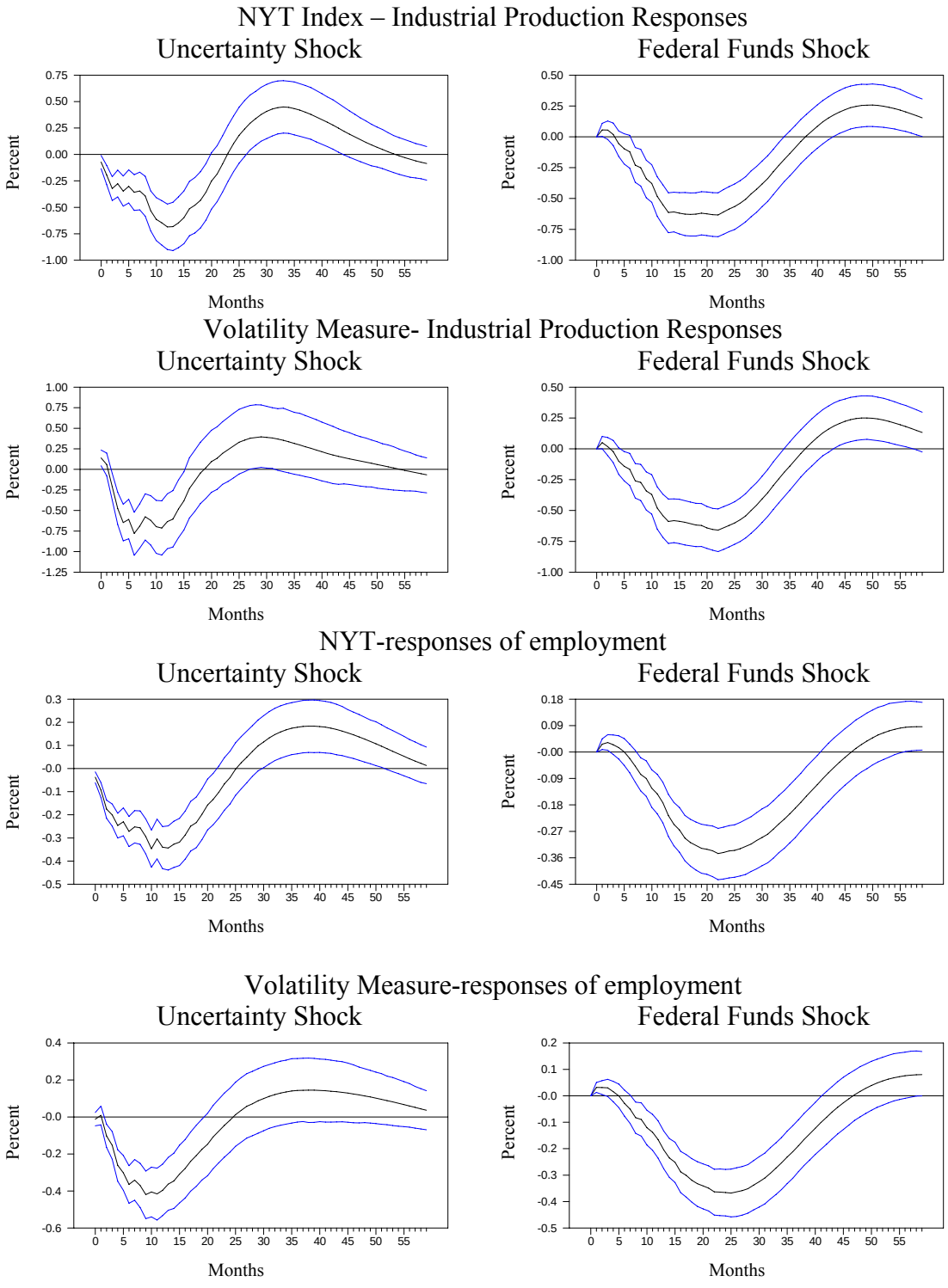
Notes: Each panel depicts the variable's response to a one standard deviation shock and includes one standard deviation error bands.

Figure 4. Response of Variables to Uncertainty Shocks – Multivariate Case



Notes: Each panel depicts the variable's response to a one standard deviation shock and includes one standard deviation error bands.

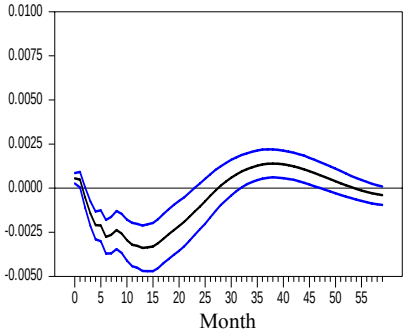
Figure 5: Uncertainty shocks vs. Monetary Policy shocks



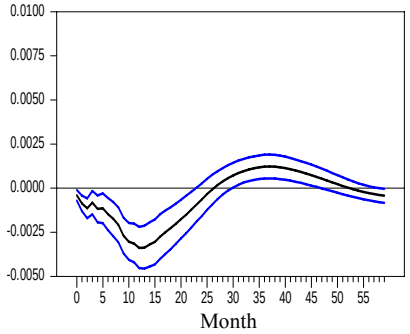
Notes: Each panel includes one standard deviation error bands. The Federal Funds (Monetary) shock increases the Federal Funds Rate by 1%, and the Uncertainty Shock increases the Uncertainty Measures by 50%

Figure 6. Response of Variables to Uncertainty Shocks –Tri variate Case (Volatility ordered before Article Index)

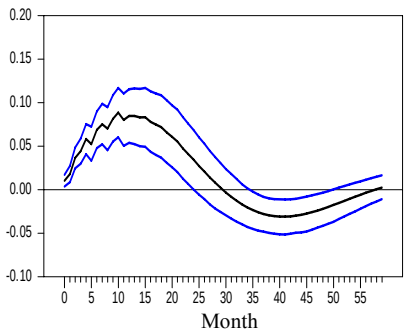
Volatility
Industrial Production



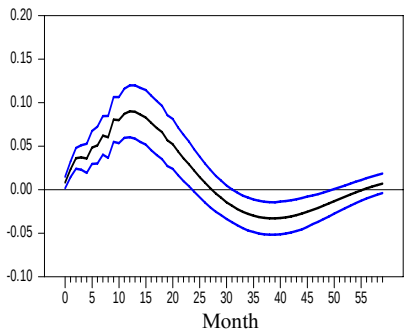
NYT
Industrial Production



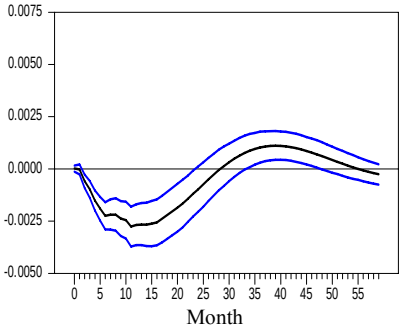
Volatility
Unemployment



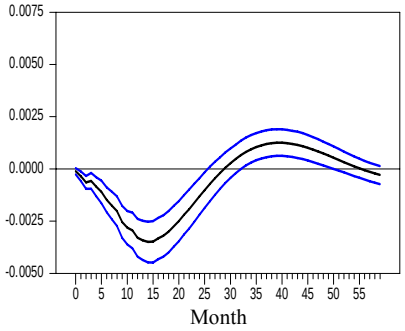
NYT
Unemployment



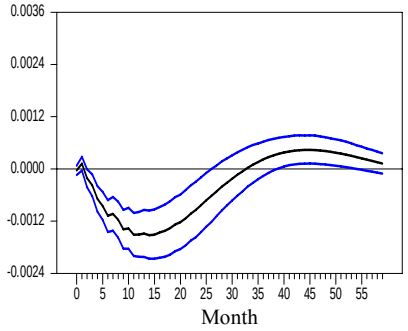
Volatility
Manufacturing Employment



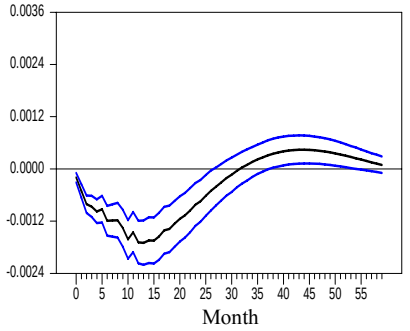
NYT
Manufacturing Employment



Volatility
Employment



NYT
Employment

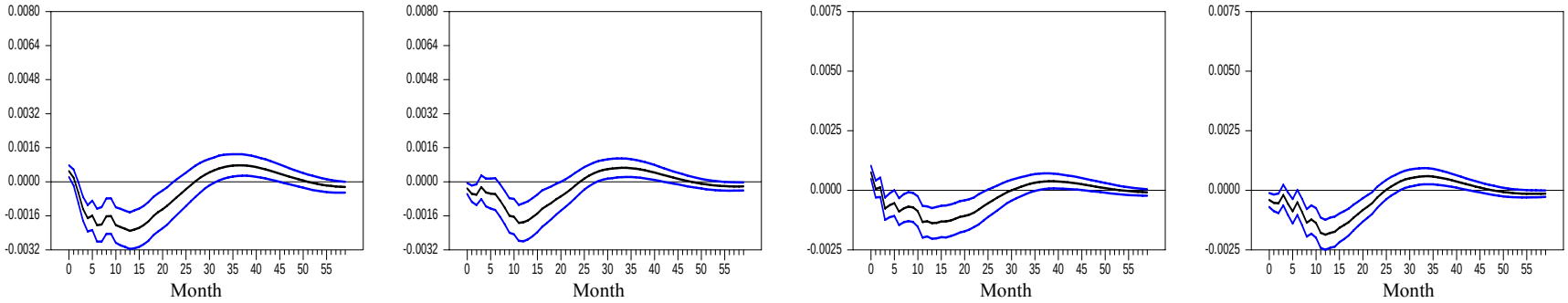


Volatility
Output per worker

NYT
Output per worker

Volatility
Output per hour

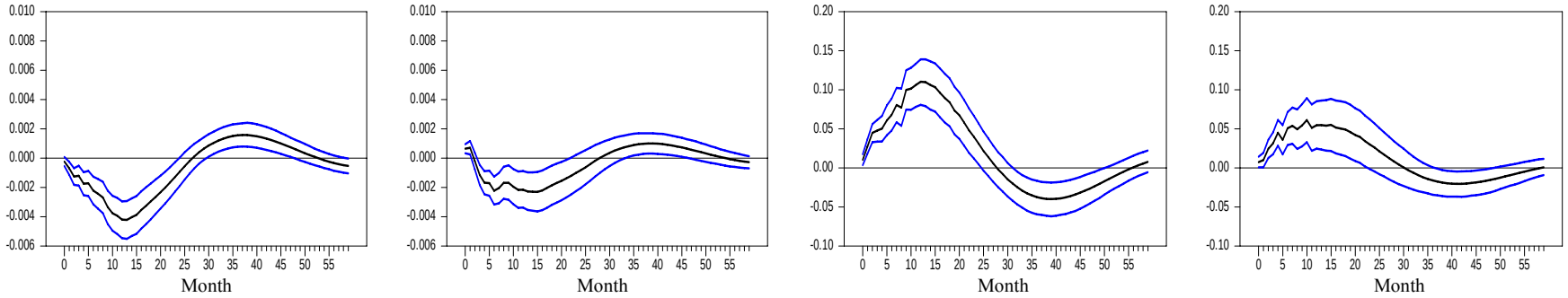
NYT
Output per hour



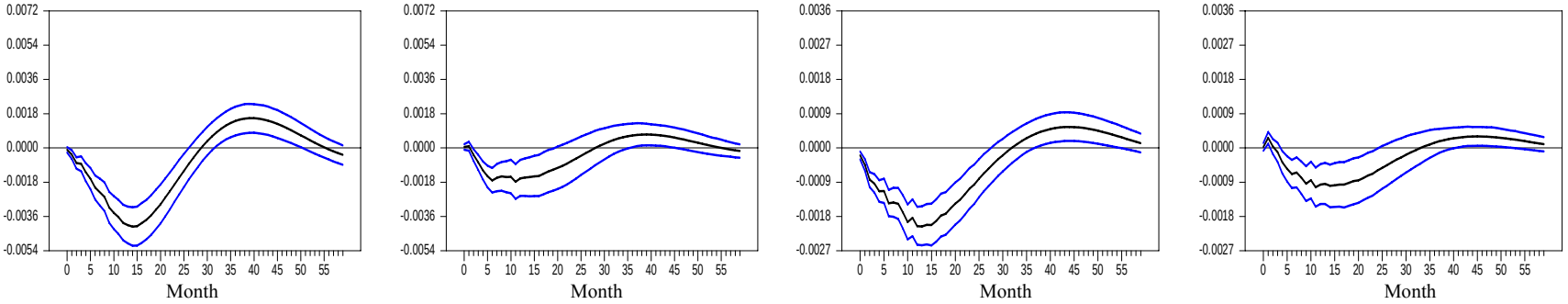
Notes: Each panel depicts the variable's response to a one standard deviation shock and includes one standard deviation error bands.

Figure 7. Response of Variables to Uncertainty Shocks –Tri-variate Case (Article Index ordered before Volatility)

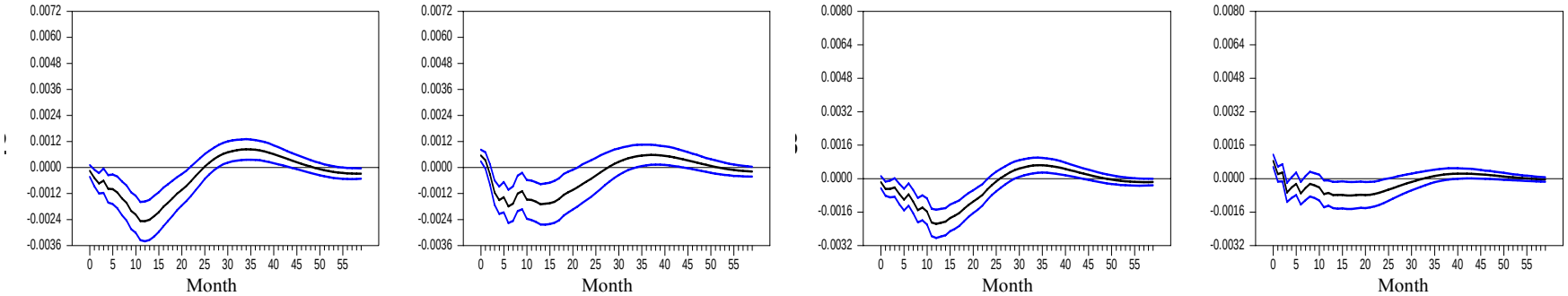
NYT Industrial Production | Volatility Industrial Production | NYT Unemployment | Volatility Unemployment



NYT Manufacturing Employment | Volatility Manufacturing Employment | NYT Employment | Volatility Employment

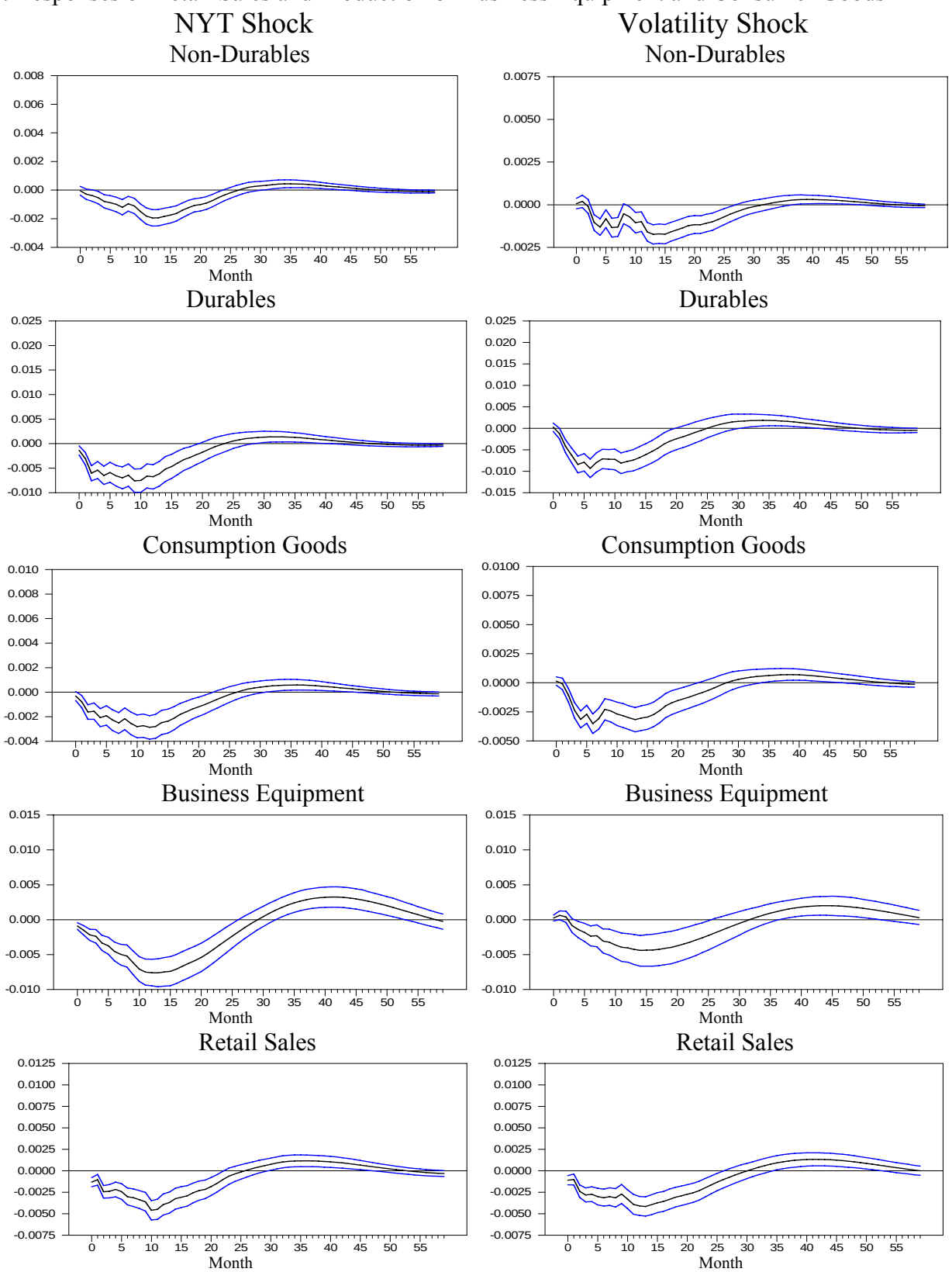


NYT Output per worker | Volatility Output per worker | NYT Output per hour | Volatility Output per hour



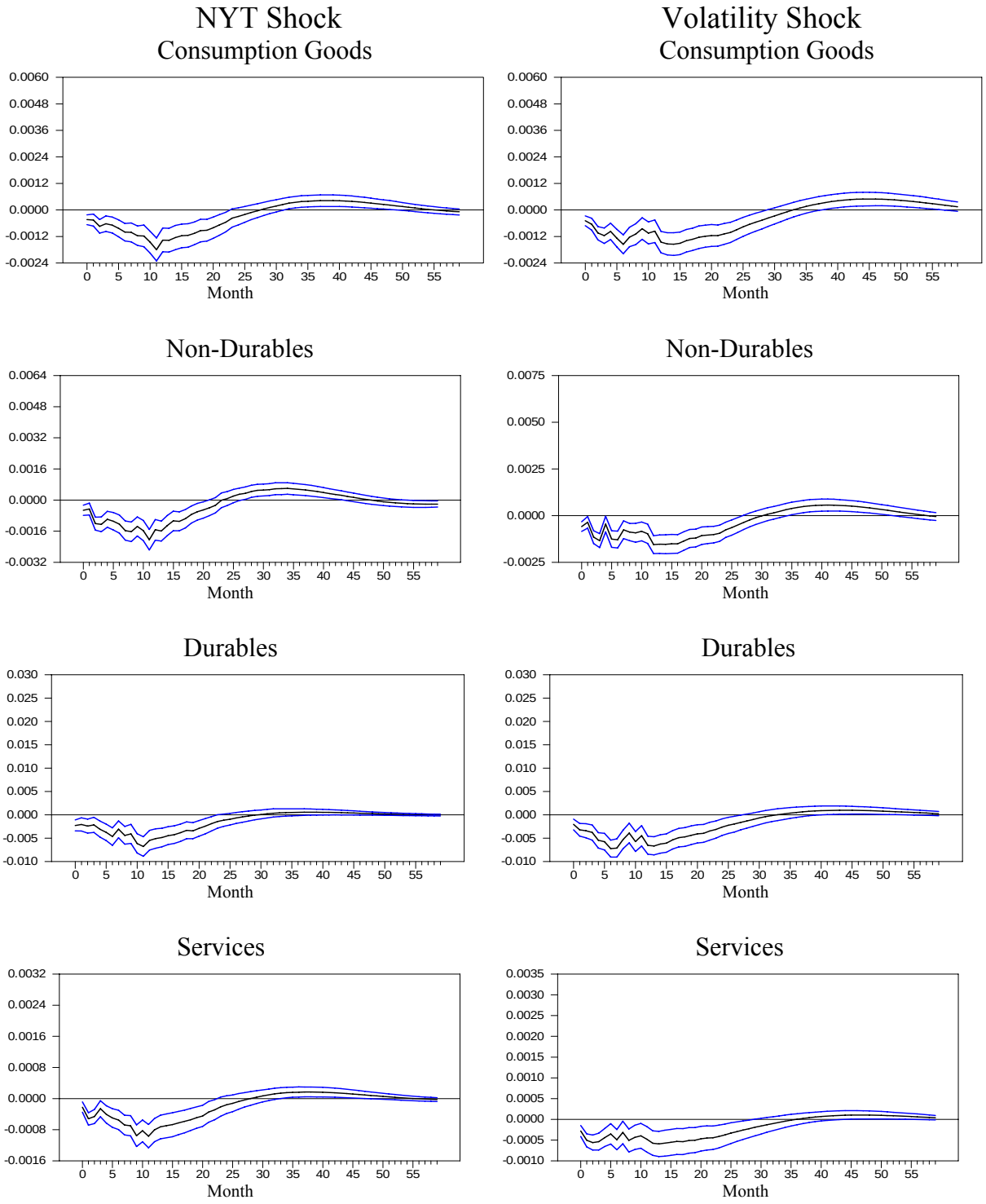
Notes: Each panel depicts the variable's response to a one standard deviation shock and includes one standard deviation error bands.

Figure 8. Responses of Retail Sales and Production of Business Equipment and Consumer Goods



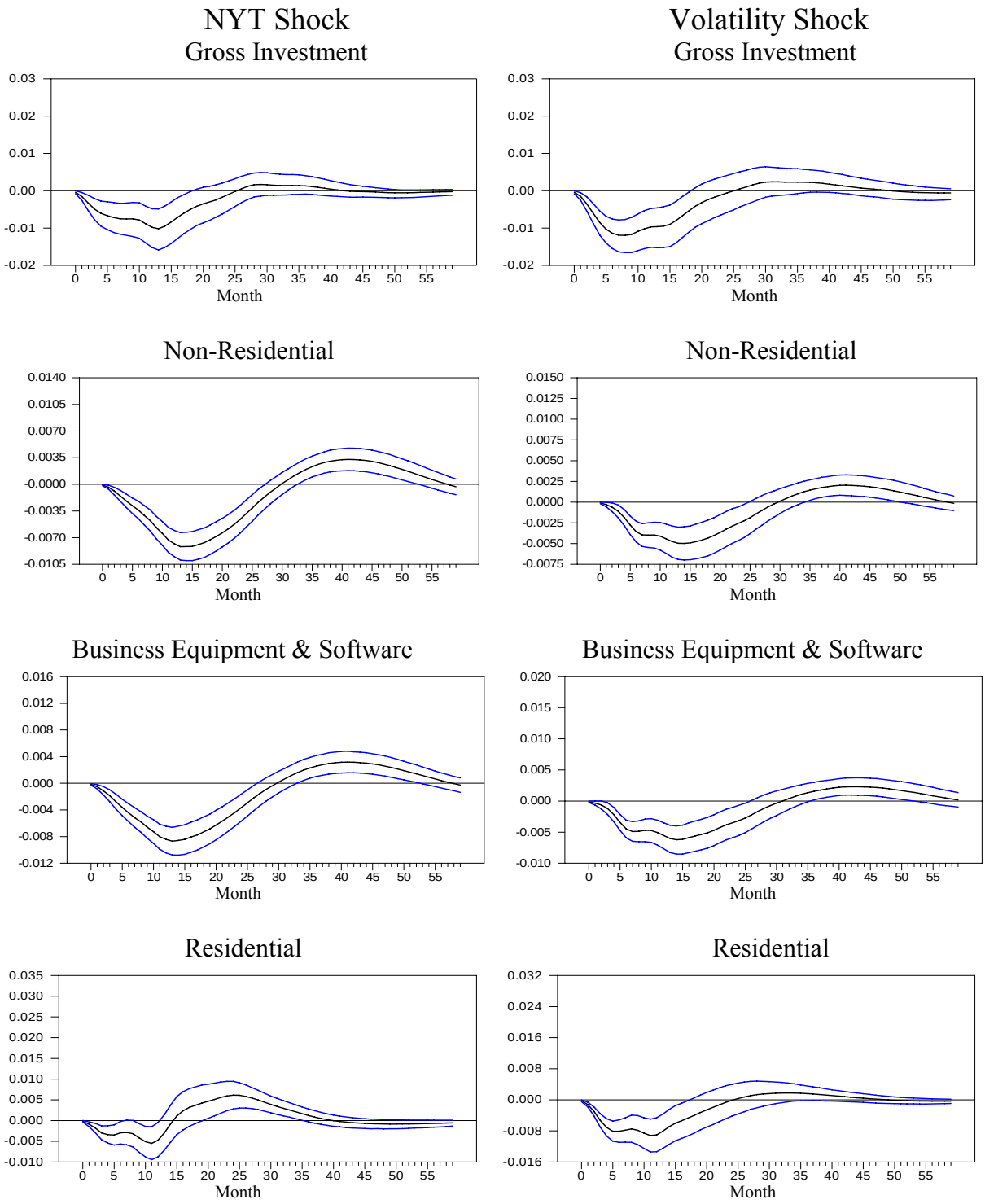
Notes: Each panel depicts the variable's response to a one standard deviation shock and includes one standard deviation error bands.

Figure 9. Responses of Consumption Expenditures



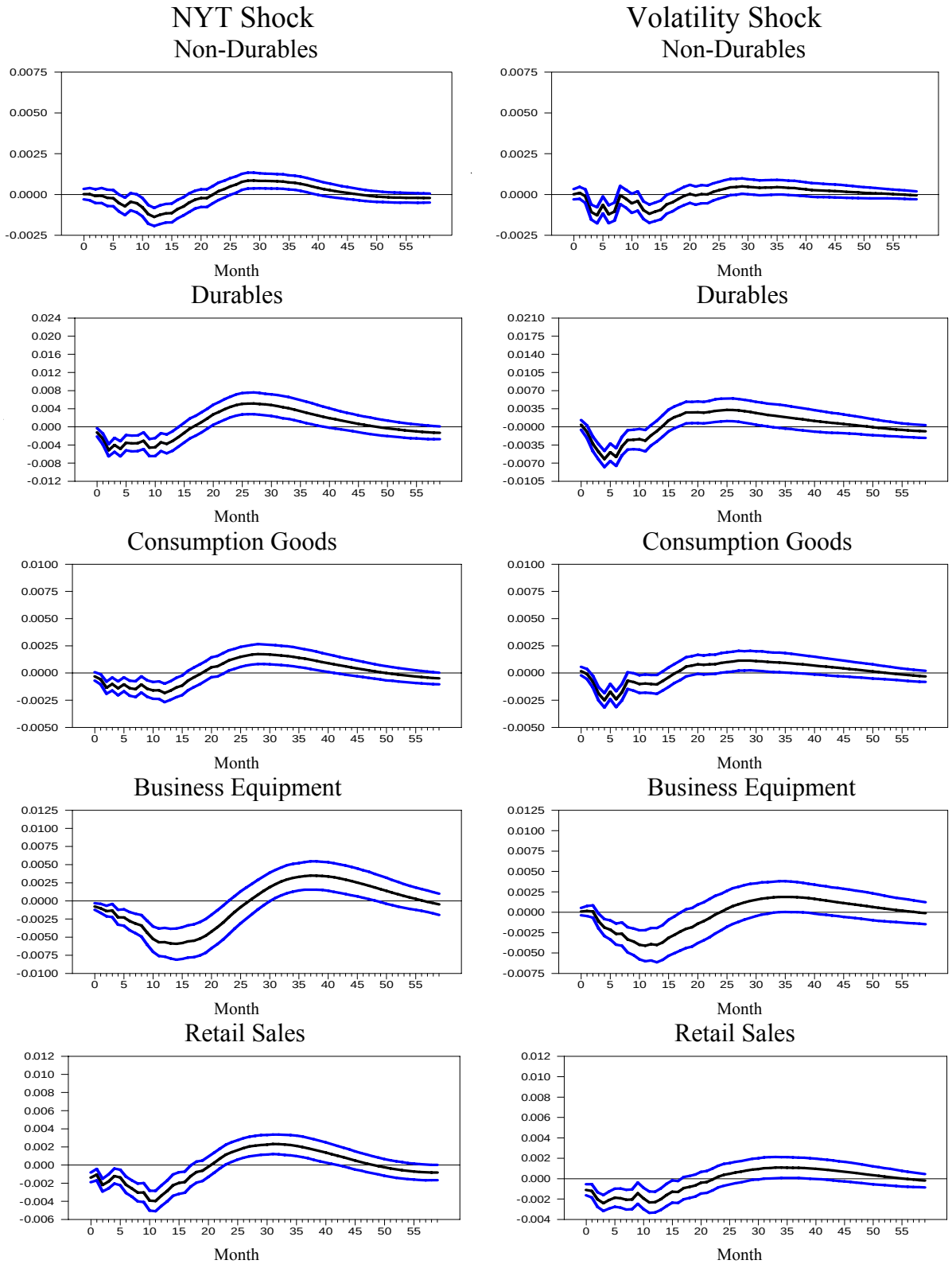
Notes: Each panel depicts the variable's response to a one standard deviation shock and includes one standard deviation error bands.

Figure 10. Responses of Investment



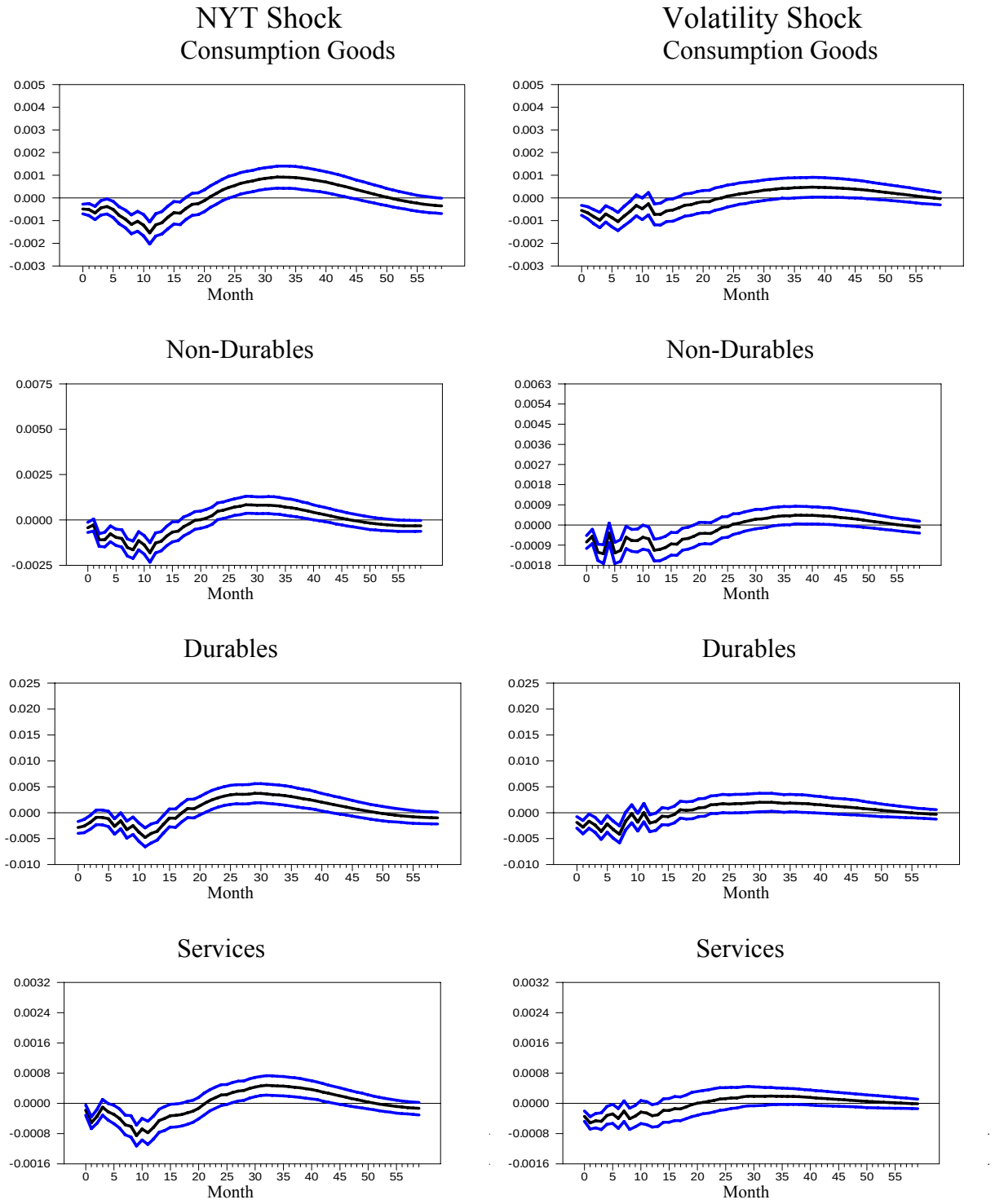
Notes: Each panel depicts the variable's response to a one standard deviation shock and includes one standard deviation error bands.

Figure 11. Responses of Retail Sales, Business Equipment, and Consumer Goods – Multi-variate Case



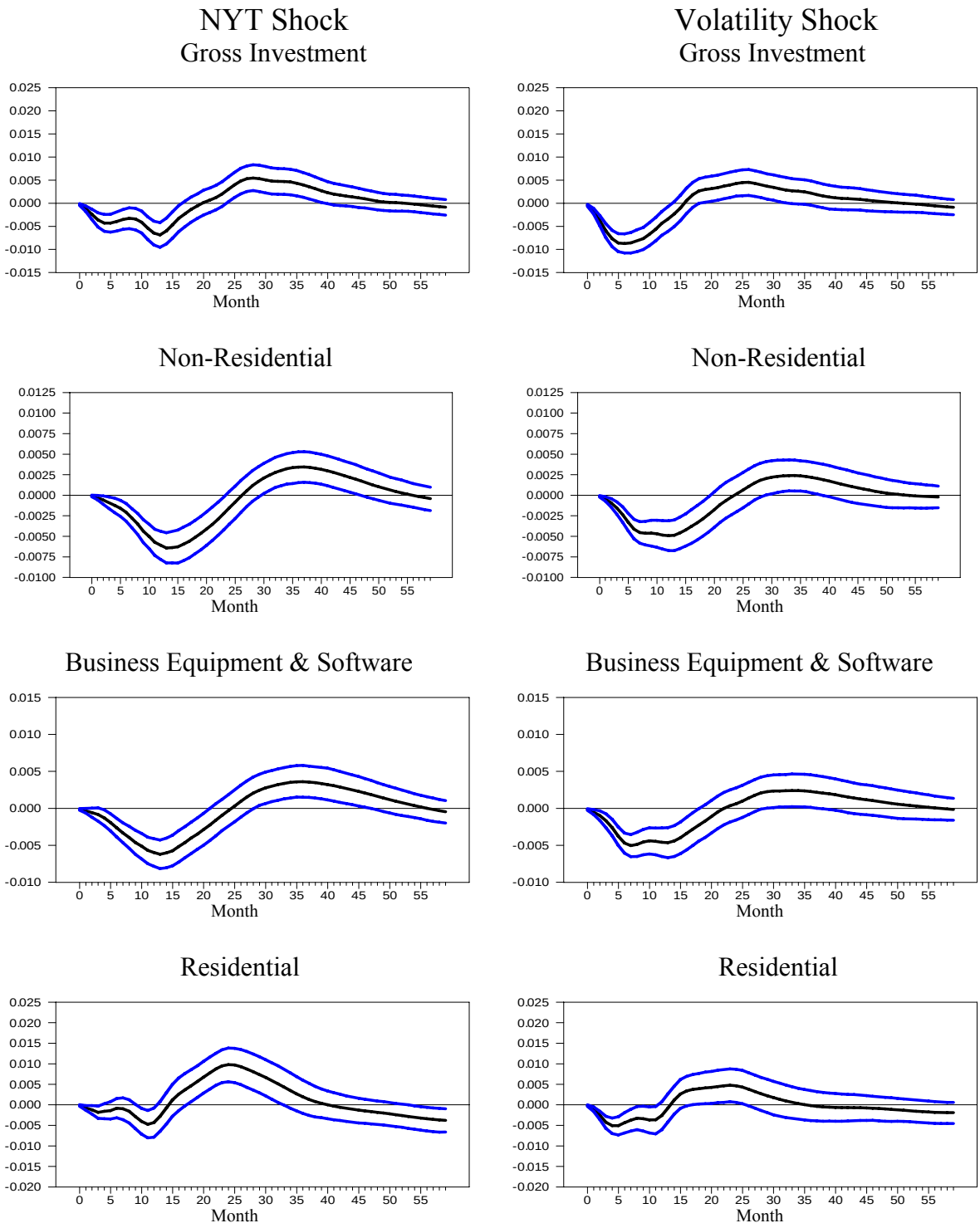
Notes: Each panel depicts the variable's response to a one standard deviation shock and includes one standard deviation error bands.

Figure 12. Responses of Consumption – Multi-variate Case



Notes: Each panel depicts the variable's response to a one standard deviation shock and includes one standard deviation error bands.

Figure 13. Responses of Investment – Multi-variate



Notes: Each panel depicts the variable's response to a one standard deviation shock and includes one standard deviation error bands.