News-driven Business Cycles: Evidence from Investor Expectations of Future Stock Market Returns*

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Abstract

This paper uses a time series of investors' expectations of the future stock market, which is proposed by Greenwood and Shleifer (2014), as a new proxy for expectations of future economic developments. Incorporating this measure of expectations into otherwise standard VAR models and implementing the approach of sign restrictions to identify news shocks, we provide empirical evidence in favor of the news-driven business cycles hypothesis. New shocks identified by exploiting movements in the measure of investors' expectations are found to induce a generalized boom of the economy that is associated with delayed and permanent increases in total factor productivity, but not with its current improvements.

JEL Classification: E1, E3

Keywords: news-driven business cycles, a measure of investors' expectations of future stock market returns, news shocks, sign restrictions

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1 Introduction

Most of the modern theories of the business cycle have a view that fluctuations in aggregate variables are driven by changes in current fundamentals.[1] On the other hand, the news-driven business cycle view is that business cycles might arise on the basis of changes in expectations of future fundamentals.[2] This news view has a long tradition in the macroeconomic literature, as reflected by the work of Pigou (1926).

In the empirical literature on the news view of business cycles, two forward-looking variables, stock prices and consumer confidence, have been widely used to capture news about future fundamentals. In their seminal work, Beaudry and Portier (2006) use the Standard and Poor's 500 composite index as a measure of stock prices that is viewed to be a good indicator of agents' expectations about future economic conditions, and exploit movements in stock prices to expand the understanding of the role of expectations in business cycle fluctuations. They document that disturbances that represent innovations to stock prices, which are orthogonal to innovations in total factor productivity (TFP), predict delayed and permanent improvements in TFP, drive standard business cycle comovements, and explain a large fraction of business cycle fluctuations, thereby providing empirical evidence in favor of news-driven business cycles.

Consumer confidence is also viewed to be a good variable for conveying news about future fundamentals such as productivity. Barsky and Sims (2012) explore innovations in consumer confidence, which is measured by the Michigan Survey of Consumers index of consumer confidence in the economy for the next years, to examine the news view of business cycle fluctuations. They document that innovations to consumer confidence entirely reflect the

[1] The most commonly discussed driving forces of business cycles are surprise changes in technology shocks (e.g., Robert and King, 1984), disembodied technology shocks (e.g., Fisher, 2002), investment-specific technology shocks (e.g., Fisher 2006), non-technological shocks such as monetary policy shocks (e.g., Gali, 1999), and demand shocks (e.g., Christiano and Eichenbaum, 1992).

[2] For example, see Cochrane (1994), Beaudry and Portier (2004), Jaimovich and Rebelo (2008 and 2009), Haan and Kaltenbrunner (2009), Lorenzoni (2011), and Kurmann and Otrok (2013).

news component of future economic conditions, especially changes in expected productivity growth over a relatively long horizon, and such fundamental news is the main driving force of fluctuations in real economic activities.

In this paper, we use a time series of investors' expectations of future stock market returns, which is proposed by Greenwood and Shleifer (2014), as a proxy for capturing news about future economic developments. This series of expectations is constructed from the American Association of Individual Investor Sentiment Survey (AAIISS) data. The AAIISS measures the percentage of individual investors who are bullish, neutral, or bearish on the stock market for the next six months, and then an index is constructed by subtracting the percentage of "bearish" investors from the percentage of "bullish" investors. So this index represents a measure of investors' expectations of the future stock market. By exploiting movements in the measure of investors' expectations, we re-examine the role of expectations in business cycle fluctuations. For this purpose, we incorporate this survey measure of expectations into otherwise standard vector autoregressive (VAR) models, and identify news shocks by implementing the approach of sign restrictions.

Our VAR models include TFP, the inflation rate, the nominal interest rate, and other real aggregate variables as well as the measure of investors' expectations. In VAR models, we identify news shocks by imposing the positive sign restriction on the impact response of the survey measure of investors' expectations, the zero restriction on the impact response of TFP, the negative sign restriction on the impact response of the inflation rate, and the zero restriction on the impact response of the nominal interest rate. We leave the responses of all other aggregate variables unrestricted. In particular, the negative impact restriction on the inflation rate and zero impact restriction on the nominal interest rate are imposed to differentiate non-inflationary news shocks from expansionary monetary and demand shocks. In sum, our identification strategy is designed to identify news shocks, orthogonal to innovations to TFP, that are not likely to be confounded by monetary and demand shocks.

Our empirical results show that the measure of investors' expectations jumps up sharply on impact of our identified news shocks and declines over time. TFP eventually rises to a higher long-run level, although it does not rise significantly about zero until almost ten quarters following the news shock. Consumption rises immediately following the news shock and continues to rise to a permanently higher level, although its impulse response is unrestricted. Hours worked barely change on impact but increase gradually over time, thereby exhibiting a hump-shaped response before converging back to the initial level. Investment and output display a similar hump-shaped pattern as hours worked, and converge to their new long-run levels. Our findings indicate that identified news shocks induce a broad economic boom that is associated with delayed increases in TFP, lending credence to the news-driven business cycle hypothesis.

In our identifying strategy, the positive sign restriction on the impact response of the measure of investors' expectations is interpreted as capturing news about future fundamentals. When removing this restriction from the set of our identifying restrictions, TFP is found not to rise to a permanent higher level with a delay following the news shock. Instead, it appears to increase immediately for the very short period of time. Initial booms in consumption, hours, investment, and output are very temporary. This finding suggests that exploiting innovations to our measure of investors' expectations is of help to isolate news shocks that predict delayed but permanent increases in TFP and induce a generalized boom of the economy.

We also consider the VAR models that are obtained by substituting stock prices or consumer confidence in place of the measure of investors' expectations. In such VAR models, we impose the positive sign restriction on the impact response of stock prices or consumer confidence as well as the same restrictions on three other variables to identify news shocks. The results from these exercises show that exploiting movements in stock prices, consumer confidence, or the survey measure of investor expectations generates the similar patterns of the impulse responses of TFP and aggregate variables to news shocks. Nonetheless, there are some quantitative differences in estimated impulse responses across these three forward-looking variables whose movements are actually exploited to capture news about future fundamentals.

The remainder of this paper is organized as follows. Section 2 briefly introduces the approach of sign restrictions, describes the data used in our empirical study, and details the set of sign and zero restrictions we impose to identify news shocks. Section 3 presents our empirical results and discuss them. Section 4 contains conclusions.

2 Empirical Strategy

2.1 Sign Restrictions

In this subsection, we briefly introduce the approach of sign restrictions to identify news shocks, a particular structural shock of interest in this paper. The basic idea of this approach is to impose sign restrictions on the impulse responses of a set of variables as a means of recovering structural shocks of interest. It has been widely used in the recent empirical SVAR studies. For instance, Mountford and Uhlig (2009) use the sign restriction approach to identify non-fiscal shocks and fiscal policy shocks. In their study, fiscal policy shocks are identified through restricting the impulse responses of the fiscal variables and through the requirement that they are orthogonal to both business cycle shocks as well as monetary policy shocks.

To discuss the approach of sign restrictions, let us begin with the following reduced-form VAR model:

$$Y_t = \mu + \sum_{k=1}^{p} \Phi_k Y_{t-k} + u_t, \tag{1}$$

where Y_t is an $n \times 1$ vector of variables, Φ_k is an $n \times n$ reduced-form VAR coefficient matrix, and u_t is reduced-form innovations with the variance-covariance matrix Σ_u (i.e., $E\left[u_t u_t'\right] = \Sigma_u$).

The reduced-form moving-average representation is expressed as:

$$Y_t = \mu + \sum_{h=0}^{\infty} B(h)\, u_{t-h}, \tag{2}$$

where $B(0) = I_n$. The common assumption is that there is a linear mapping between reduced-form innovations u_t and economically meaningful structural shocks ϵ_t:

$$u_t = A_0 \epsilon_t, \tag{3}$$

where n structural shocks are mutually orthogonal and normalized to be equal to one (i.e., $E\left[\epsilon_t \epsilon_t'\right] = I_n$), and the impact matrix A_0 satisfies $A_0 A_0' = \Sigma_u$. Alternatively, the impact matrix can be rewritten as:

$$A_0 = \widetilde{A}_0 Q, \tag{4}$$

where $\widetilde{A}_0$ is any arbitrary orthogonalization of Σ_u (e.g., $\widetilde{A}_0$ is the Cholesky decomposition of Σ_u), and Q is an orthonormal matrix (i.e., $QQ' = I$). Identifying structural shocks ϵ_t (or a particular structural shock of interest) amounts to pinning down the orthonormal matrix Q (or a column of Q, i.e., a unit vector denoted by q) by imposing identifying restrictions.

Using Equations (2), (3), and (4), the structural moving-average representation can be written as:

$$Y_t = \sum_{h=0}^{\infty} R(h)\, \epsilon_{t-h}, \tag{5}$$

where $R(h) = C(h)\, Q$ with $C(h) = B(h)\, \widetilde{A}_0$. Therefore, the impulse response vector of variables to a structural shock that corresponds to the j^{th} element of ϵ_t at horizon h is the j^{th} column of $R(h)$, which is denoted by $r^{(j)}(h)$:

$$r^{(j)}(h) = C(h)\, q^{(j)}, \tag{6}$$

where $q^{(j)}$ is the j^{th} column of Q. The impulse response of variable i to structural shock j at horizon h is the i^{th} element of $r^{(j)}(h)$, which is denoted by $r_i^{(j)}(h)$:

$$r_i^{(j)}(h) = C_i(h)\, q^{(j)}, \tag{7}$$

where $C_i(h)$ is the i^{th} row of $C(h)$.

A structural shock of interest is identified by imposing sign restrictions on impulse responses of selected variables to this shock (i.e., $r_i^{(j)}(h)$) for some horizons $h = \underline{h}_i, \cdots, \overline{h}_i$, following the shock. It follows from Equation (7) that this is equivalent to identifying the unit vector $q^{(j)}$ that satisfies the imposed sign restrictions as much as possible. In particular, we take the penalty-function approach proposed by Uhlig (2005) and Mountford and Uhlig (2009) that minimizes a criterion function for sign restriction violations. An attractive feature of this approach is that it allows us to easily incorporate zero restrictions in addition to sign restrictions. We skip the details of their penalty-function approach and numerical algorithms to save space and refer Uhlig (2005) and Mountford and Uhlig (2009) for more information.

2.2 Data

We use quarterly US data from the sample period spanning 1987:Q3 to 2011:Q4. Our sample period is dictated by the availability of the data.[3] Our dataset contains the following ten variables: expectations of future fundamentals, stock prices, consumer confidence, total

[3] Our measure of expectations of future fundamentals are available only for this sample period.

factor productivity (TFP), consumption, investment, output, hours worked, the inflation rate, and the nominal interest rate. This subsection describes this set of variables used in our empirical study.

2.2.1 A Measure of Investor Expectations of Future Stock Market Returns

In this paper, we use a time series of investor expectations of future stock market returns proposed by Greenwood and Shleifer (2014) as a measure of expectations of future fundamentals. Greenwood and Shleifer collect survey results from six major sources (i.e., the Gallup investor survey, Graham and Harveys surveys of CFOs, the American Association of Individual Investors (AAII) survey, Investor Intelligences summary of professional investors beliefs, Shillers survey on individual investors, and the University of Michigan), and then construct six survey measures of investor expectations. These six measures of expectations are shown to be highly correlated with each other, as well as the level of the stock market. Moreover, they document that survey measures of expectations are reflections of widely shared beliefs about future market returns, which tend to be extrapolative in nature. It suggests that each of their survey measures is a good proxy for expectations of future economic developments.

The measure of investor expectations used in this paper is one obtained from the AAII survey data because it is publicly available and has the longest period among six measures of expectations proposed by Greenwood and Shleifer. The AAII survey measures the percentage of individual investors who are bullish, neutral, or bearish on the stock market for the next six months and is administered weekly to members of the AAII. The measure of expectations denoted by AA is constructed by subtracting the percentage of "bearish" investors from the percentage of "bullish" investors:

$$AA = \%Bullish - \%Bearish$$

Figure 1 shows this measure of investor expectations of future stock market returns, indicating that it starts to fall before US recessions.

2.2.2 Other Aggregate Variables

Our measure of stock prices is the end-of-period Standard and Poor's 500 (S&P 500) composite index divided by CPI of all items for all urban consumers. The S&P 500 series is obtained from the *Wall Street Journal*, and the CPI series is obtained from the Bureau of Labor Statistics (BLS).

As in Barsky and Sims (2011, 2012), we use the question in Table 29 of the Survey of Consumers by the University of Michigan as a measure of consumer confidence in economy for the next five years.[4] This measure is denoted by E5Y.

Our TFP measure is the factor-utilization-adjusted TFP series first developed by Basu, Fernald, and Kimball (2006) and updated on John Fernald's website. Non-capacity-utilization-adjusted TFP series is also available on the website. In general, the adjusted TFP series is believed to be a much better measure of true technological progress, so that we take it as our measure of TFP.

Consumption is measured by real consumption expenditures on nondurable goods and services from the Bureau of Economic Analysis (BEA). Investment is measured by real gross private domestic investment from the BEA. Output is measured by real output in the non-farm business sector from the BLS. Hours worked is measured by total hours worked of all persons in the non-farm business sector obtained from the BLS. These four variables (i.e., consumption, investment, output, and hours worked) are transformed in per capita terms by dividing each of them by the civilian non-institutionalized population aged sixteen and over. The population data is from the BLS.

[4]Column Relative in Table 16 of the survey summarizes responses to the forward-looking question: Looking ahead, which would you say is more likely - that in the country as a whole we will have continuous good times during the next 5 years or so, or that we will have periods of widespread unemployment or depression, or what?" The series is constructed as the percentage of respondents giving a favorable answer minus the percentage giving an unfavorable answer plus 100.

The inflation rate is measured by the annualized quarterly CPI growth rate, and the nominal interest rate is the effective federal funds rate from the Federal Reserve Board.

2.2.3 Identification Strategy

Our baseline VAR model contains six variables: investor expectations of future stock market returns as a measure of expectations of future fundamentals, TFP, the inflation rate, the nominal interest rate, consumption, and an aggregate variable of interest. Hours worked, investment, and output are considered as the variable of interest in the model at a time. Except for the measure of expectations, interest rate and inflation rate, all variables are logged and enter the model in levels. A constant and four lags are also included in the model. The results are robust to different numbers of lags.

Our identification strategy is described in Table 1. To identify news shocks, we impose a set of sign and zero restrictions on the impact responses of the measure of expectations, TFP, the inflation rate, and the nominal interest rate, while leaving the responses of all other variables unrestricted. These restrictions are supported by previous studies on news-driven business cycles. The positive sign restriction on the impact response of the measure of expectations is imposed to pick up positive innovations in expectations of future fundamentals. The zero restriction on the impact response of TFP ensures that news shocks are orthogonal to current improvements in technological opportunities. This zero impact restriction have been widely used in the previous SVAR studies on news shocks (e.g., Beaudry and Portier (2006), Barsky and Sims (2011), and Nam and Wang (2019)). Based on the well-documented fact that news-driven booms are non-inflationary, the negative sign restriction on the impact response of the inflation rate is imposed. Also, the zero restriction on the impact response of the nominal interest rate is imposed to distinguish news shocks from monetary policy shocks. In particular, the zero impact restriction on the nominal interest rate and negative impact restriction on the inflation rate, which make it possible for the real interest rate defined as the nominal interest minus the inflation rate to be non-negative on impact of the news shock, helps us to differentiate news shocks from expansionary monetary policy shocks and demand shocks.

We also consider two alternative models, which are obtained by substituting the measure of investor expectations in the baseline model in place of consumer confidence or stock prices. In previous empirical studies on news shocks, these two forward-looking variables have been used as the best indicators of agents' expectations of future fundamentals and interpreted as capturing news. To identify news shocks in each of two alternative models, the positive sign restriction on the impact response of consumer confidence or stock prices is imposed to capture the effect of news shocks, and all other restrictions remain the same. The results from these two alternative models are compared to those from the baseline model with the measure of investor expectations of future stock market returns.

3 Empirical Results

3.1 Results from the Baseline Model

This subsection presents the results from our baseline six-variable model that includes the survey measure of investor expectations of stock market returns as well as other five variables. News shocks are identified by implementing our sign restriction strategy as discussed in Section 2.2.3.

Figure 2 displays the impulse response functions (IRFs) to a unit increase in the news shock identified in the baseline model with hours worked being as a variable of interest. The figure also reports the IRFs of investment and output, which are estimated in the baseline model with investment or output in place of hours worked. Our IRF results echo previous findings on news shocks in Beaudry and Portier (2006) and Nam and Wang (2019), thereby giving credence to the news-driven business cycle hypothesis.

By the identifying restrictions, the survey measure of expectations rises and the inflation rate falls on impact of the news shock, while TFP and the nominal interest rate do not change on impact. Consumption also rises immediately following the news shock and continues to rise to a permanently higher level, although its impulse response is unrestricted.[5] Hours worked barely change on impact but increase gradually over time, thereby exhibiting a hump-shaped response before converging back to the initial level. The response patterns of investment and output are hump-shaped and very persistent.

An important aspect to notice in this figure is that TFP eventually rises to a higher long-run level, although it does not rise significantly about zero until almost ten quarters following the news shock. It implies that initial increases in consumption, hours, investment, and output following the identified shock are not associated with actual improvements in TFP. So such a generalized boom of the economy turns to be news-driven. During the news-driven economic boom, the short-term nominal interest rate rises and exhibits a hump-shaped response, which might suggest that the news-driven economic boom is accompanied by a contractionary monetary policy. This result is similar to Nam and Wang's (2019) finding on its response to their optimism shocks. It also suggests that

Table 2 reports the share of the forecast error variance (FEV) of each variable that is attributable to news shocks identified from the baseline model. The FEV results show that our identified news shocks play a significant role in driving aggregate macroeconomic fluctuations at business cycle frequencies. News shocks account for around 25% of the FEVs of consumption, investment, and output and almost 15% of the FEV of hours worked at horizons 8 to 40 quarters. Almost 15% of the FEV of TFP at horizon 40 is explained by news shocks. Interestingly, the share of the FEV of the inflation rate attributable to

[5]This finding is interesting. Previous studies on news shocks, for example, Barsky and Sims (2012) and Nam and Wang (2019), rely on some restrictions on consumption, based on the argument that economic agents have advance information about future economic conditions and they use such information when making consumption decisions. In contrast, we leave the impulse response of consumption unrestricted, but find that consumption responds immediately and significantly to our identified news shocks.

optimism shocks is significant, while that of the nominal interest rate is quite small.

We check the robustness of our findings in a larger VAR model. By imposing the same sign and zero restrictions, we identify news shocks in the eight-variable model that includes hours worked, investment, and output at the same time as well as other five variables. Figure 3 displays the IRF results from the eight-variable model. For the purpose of comparison, the figure also reports the IRF results from the baseline six-variable model, which are shown in Figure 2. The only noticeable change is that investment and output settle to new higher long-run levels as compared to the results from the baseline six-variable model. It suggests that including investment and output together in the model helps us to capture the permanent effect of the news shock on them.

Finally, we check the usefulness of our measure of expectations of future fundamentals to identify news shocks. For this purpose, we remove the positive restriction on the impact response of the survey measure of investor expectations from our set of identifying restrictions. Figure 4 displays the IRF results obtained by removing the positive impact restriction on the survey measure of expectations and keeping all other restrictions on TFP, the inflation rate, and the nominal interest rate. The figure indicates that removing the positive impact restriction on the survey measure of expectations changes our results significantly. TFP does not rise to a permanent higher level with a delay. Instead, it appears to increase immediately for the very short period of time. Initial booms in consumption, hours, investment, and output are very temporary. These findings suggest that using the survey measure of expectations as a proxy for expectations of future fundamentals and imposing the positive impact restriction on it are of help to isolate news shocks that predict delayed but permanent increases in TFP.

3.2 Results from Two Alternative Models

In this subsection, we consider two forward-looking information variables that have been generally viewed as the best indicators of individuals' expectations about the future and interpreted as capturing news in previous studies on news shocks. One is consumer confidence as used in Barsky and Sims (2012) and the other is stock prices as used in Beaudry and Portier (2006). To examine the extent to which these two variables help identifying news shocks as compared to our measure of investor expectations, we present the results from two alternative models, which are obtained by replacing the measure of investor expectations with consumer confidence or stock prices. To identify news shocks in alternative models, the positive sign restriction on the impact response of consumer confidence or stock prices is imposed and the same restrictions on TFP, the inflation rate, and the nominal interest rate are imposed.

Figure 5 presents the IRF results from the alternative model with consumer confidence. For the purpose of comparison, the figure also reports the IRFs estimated from the baseline model with the measure of investor expectations, which are shown in Figure 2. Note that the first panel of the figure reports the estimated IRF of consumer confidence in the alternative model as well as the estimated IRF of the measure of investor expectations in the baseline model. Overall, the IRFs estimated from the alternative model with consumer confidence are quite similar to those estimated from the baseline model with the measure of expectations. By construction, both consumer confidence and the measure of expectations jump up sharply on impact of the news shock. Following the shock, they declines over time and converge to their initial levels. The estimated IRFs of all other variables are similar across two models. It suggests that exploiting the information contents of consumer confidence also help capturing news about the future.

However, there are some noticeable differences. Following the news shock, consumer confidence declines more gradually than the survey measure of investor expectations. In addition, initial increases in real aggregate variables induced by identified news shocks through the restriction on consumer confidence are less significant than those induced by identified news shocks through the restriction on the survey measure of investor expectations. In particular, it turns out that hours worked do not rise strongly following the news shock identified by imposing the restriction on consumer confidence.

Figure 6 shows the IRF results from another alternative model with stock prices. In the figure, the IRFs estimated from the baseline model are also presented. In this alternative model, news shocks are identified by imposing the positive sign restriction on the impact response of stock prices, so that stock prices jump up significantly on impact. Following the news shock, they continue to rise with their peak at horizon of three quarters and then decline gradually over time. The IRFs of all other variables are qualitatively similar across the model with stock prices and the baseline model, but are quantitatively different. In particular, extracting news shocks by exploiting the information contents of stock prices generates more significant and persistent responses of real aggregate variables. For instance, the median responses of TFP, consumption, hours, investment and output in the model with stock prices at business cycle frequencies are almost the same as their 84th-quantile responses in the baseline model.

Taken together, all of these IRFs results indicate that exploiting movements in the survey measure of investor expectations of the stock market, the survey measure of consumer confidence about future economic conditions, or stock prices is of help to identify news shocks, and the resulting impulse responses support the news-driven business cycle hypothesis. Nonetheless, there are some quantitative differences in estimated impulse responses across these forward-looking variables whose movements are actually exploited to capture news about future fundamentals.

4 Conclusion

In the recent literature on news shocks, two forward-looking variables, consumer confidence and stock prices, have been widely used as the indicators of expectations of future developments in the economy and interpreted as capturing news about the future: for example, Barsky and Sims (2012) use the Michigan Survey's 5-year ahead consumer confidence index and Beaudry and Portier (2006) use the Standard and Poor's 500 composite index.

In this paper, we exploit movements in a survey measure of investors' expectations of the future stock market, which is proposed by Greenwood and Shleifer (2014), to examine the role of expectations in business cycle fluctuations. We incorporate this survey measure of expectations into otherwise standard VAR models, and then impose the positive sign restriction on its impact response as well as sign and zero restrictions on the impact responses of some other aggregate variables to identify news shocks.

We show that exploiting the information contents of the survey measure of investors' expectations is of help to isolate news shocks that predict delayed and permanent increases in technologies. The empirical finding is that a generalized boom in real economic activities induced by our identified news shocks is not associated with current improvements in technologies, which lends credence to the news-driven business cycle hypothesis.

We also show that exploiting innovations in our measure of investors' expectations, consumer confidence or stock prices generates the similar patterns of the impulse responses of TFP and aggregate variables to news shocks. However, we document that there are some quantitative differences in estimated impulse responses across these three forward-looking variables whose movements are actually exploited to capture news about future fundamentals.

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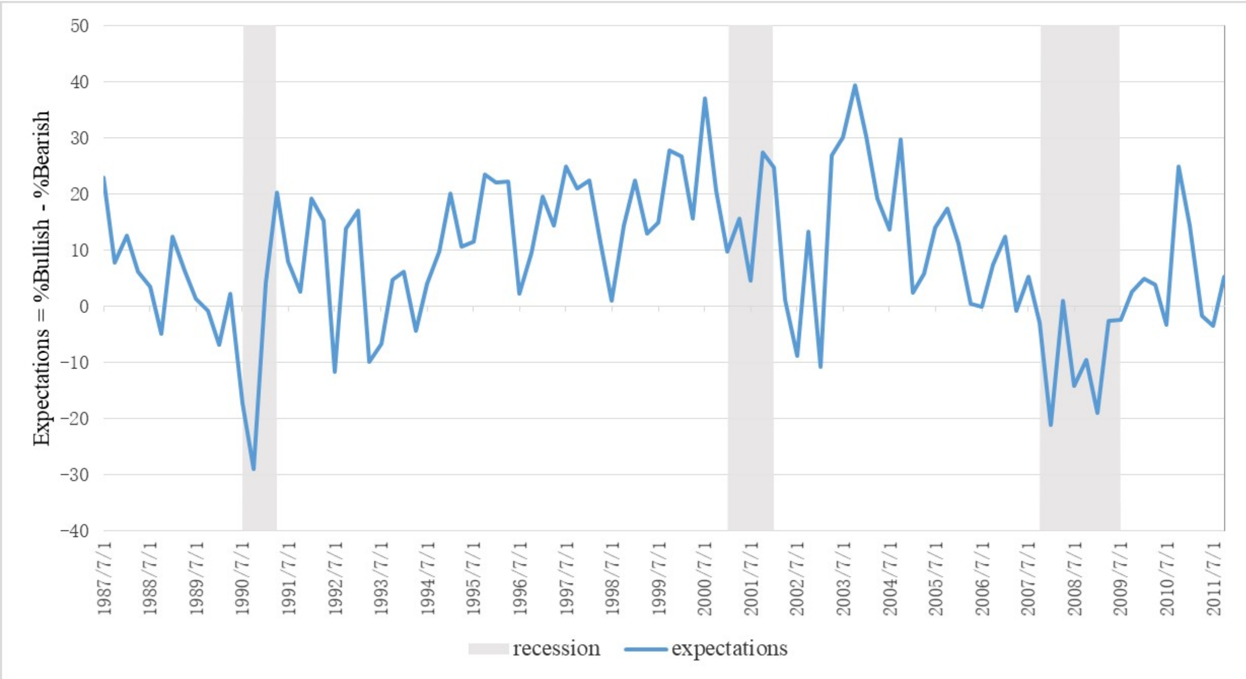
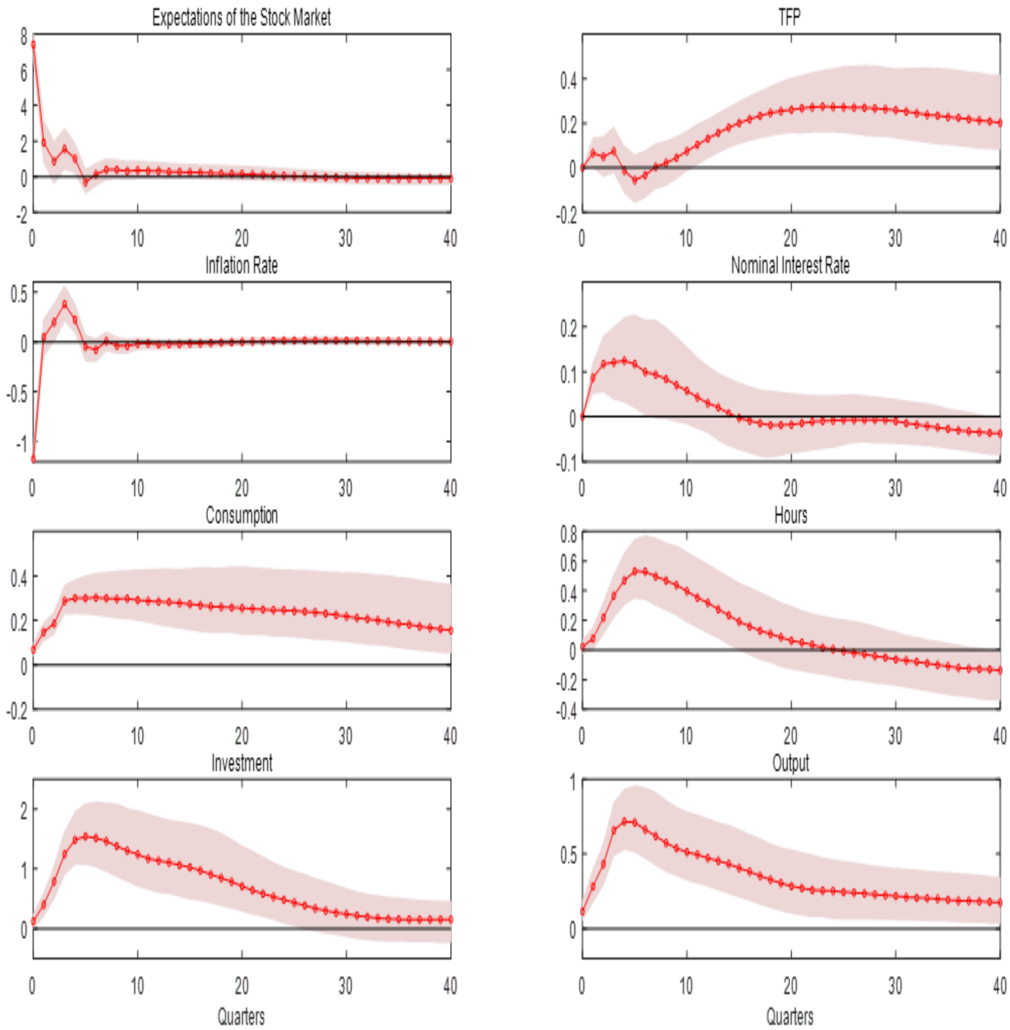
Figure 1: A Measure of Expectations of Future Stock Market Returns



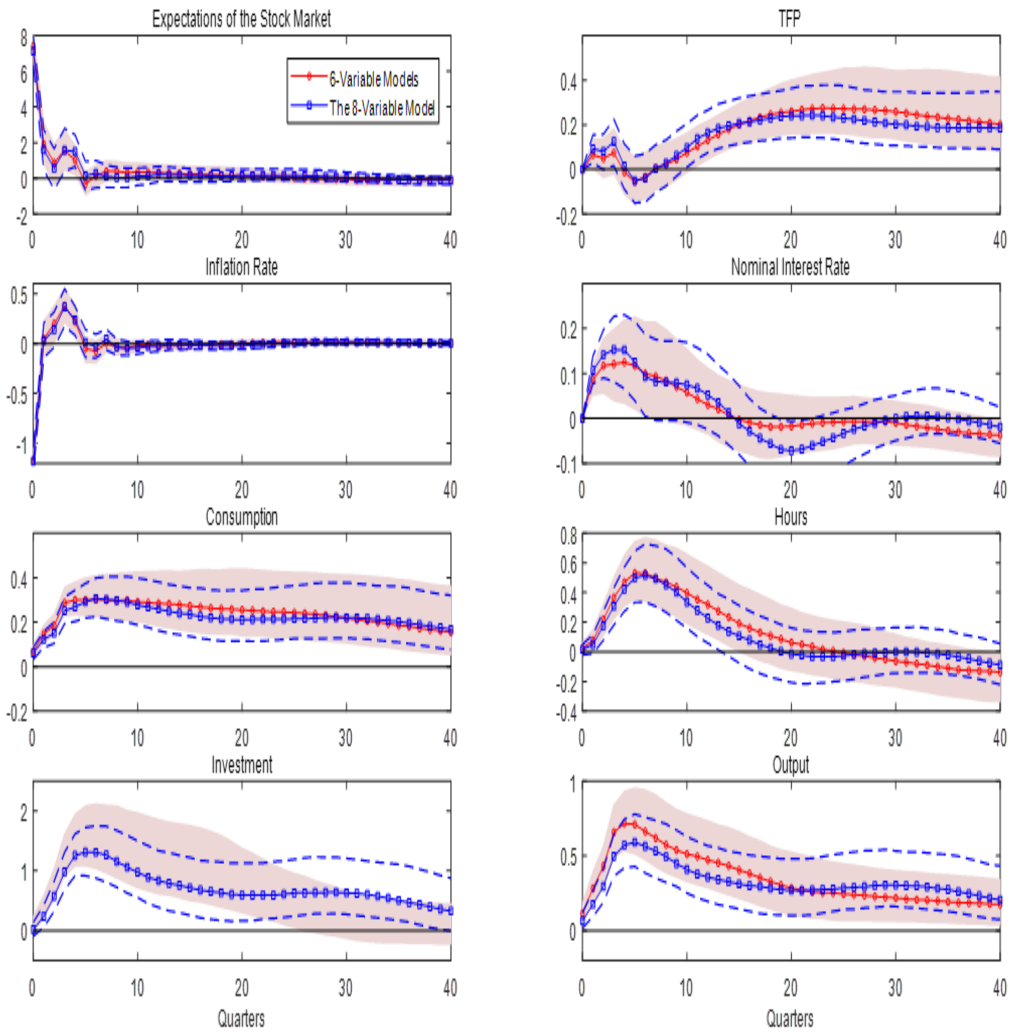
Note: This measure of expectations of future stock market returns is obtained from Greenwood and Shleifer (2014). It is based on the American Association of Individual Investor Sentiment Survey data and runs from 1987:Q3 and 2011:Q4. The gray bars indicate NBER recession periods.

Figure 2: Impulse Response Functions of the Baseline Model to a News Shock



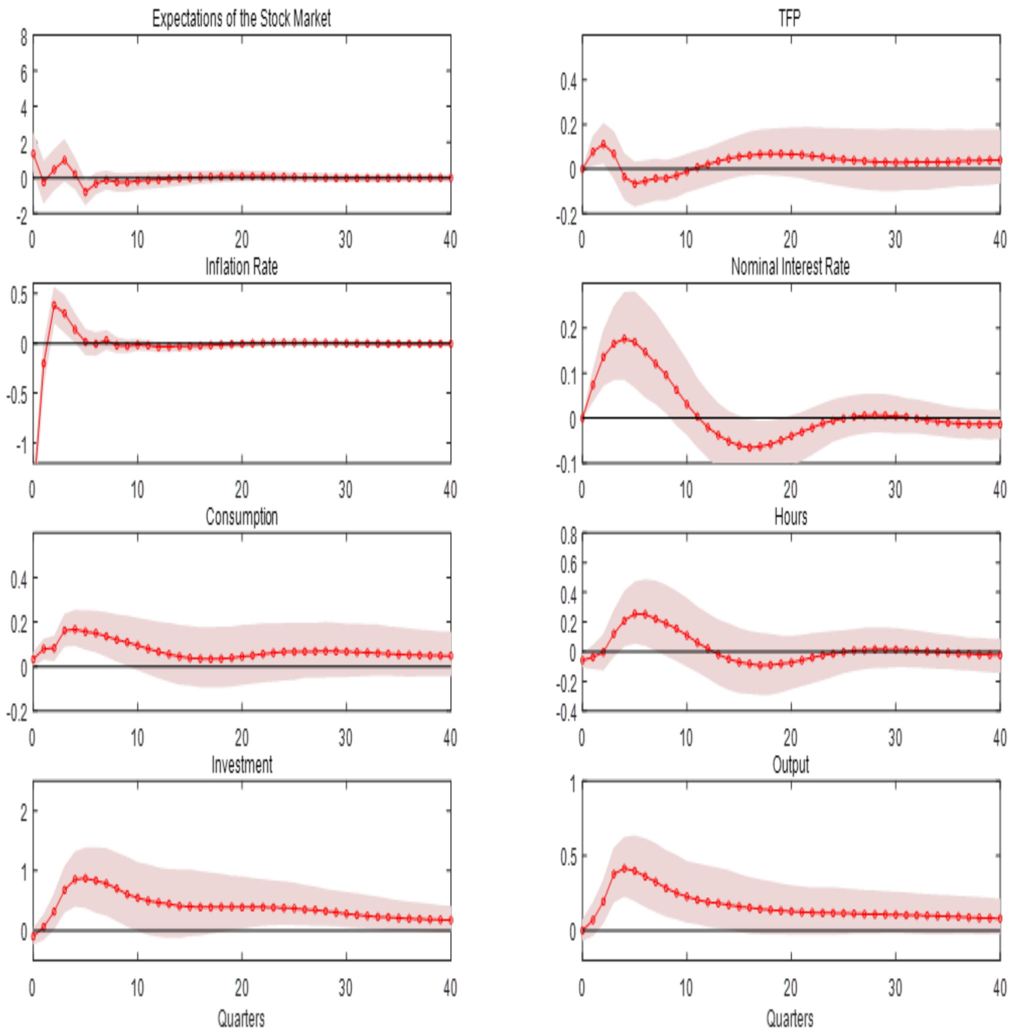
Note: This figure displays the impulse response functions to a news shock identified in the baseline model with hours worked being as a variable of interest. The figure also reports the IRFs of investment and output, which are estimated in the baseline model with investment or output in place of hours worked. The lines with circles represent median responses and colored areas represent 16th and 84th quantiles. The unit of the vertical axis is percentage deviation from the situation without shock and the unit of the horizontal axis is quarter.

Figure 3: Impulse Response Functions of a Large Model to a News Shock



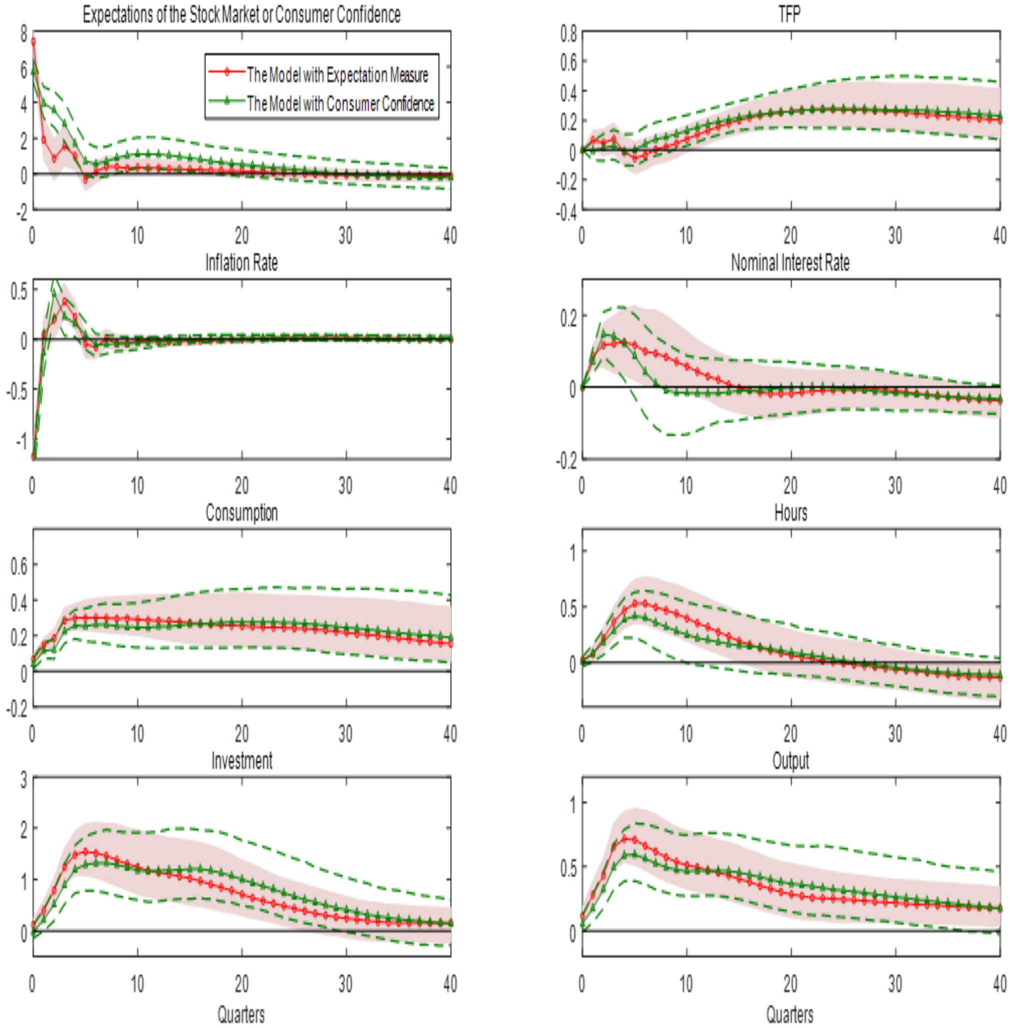
Note: This figure displays the impulse response functions (IRFs) to a news shock identified in the eight-variable model that includes hours worked, investment, and output at the same time as well as other five variables. For the purpose of comparison, the figure also reports the IRFs from the baseline six-variable model, which are shown in Figure 2.

Figure 4: Impulse Response Functions of the Baseline Model to a News Shock Identified by Removing the Impact Restriction on the Measure of Expectations



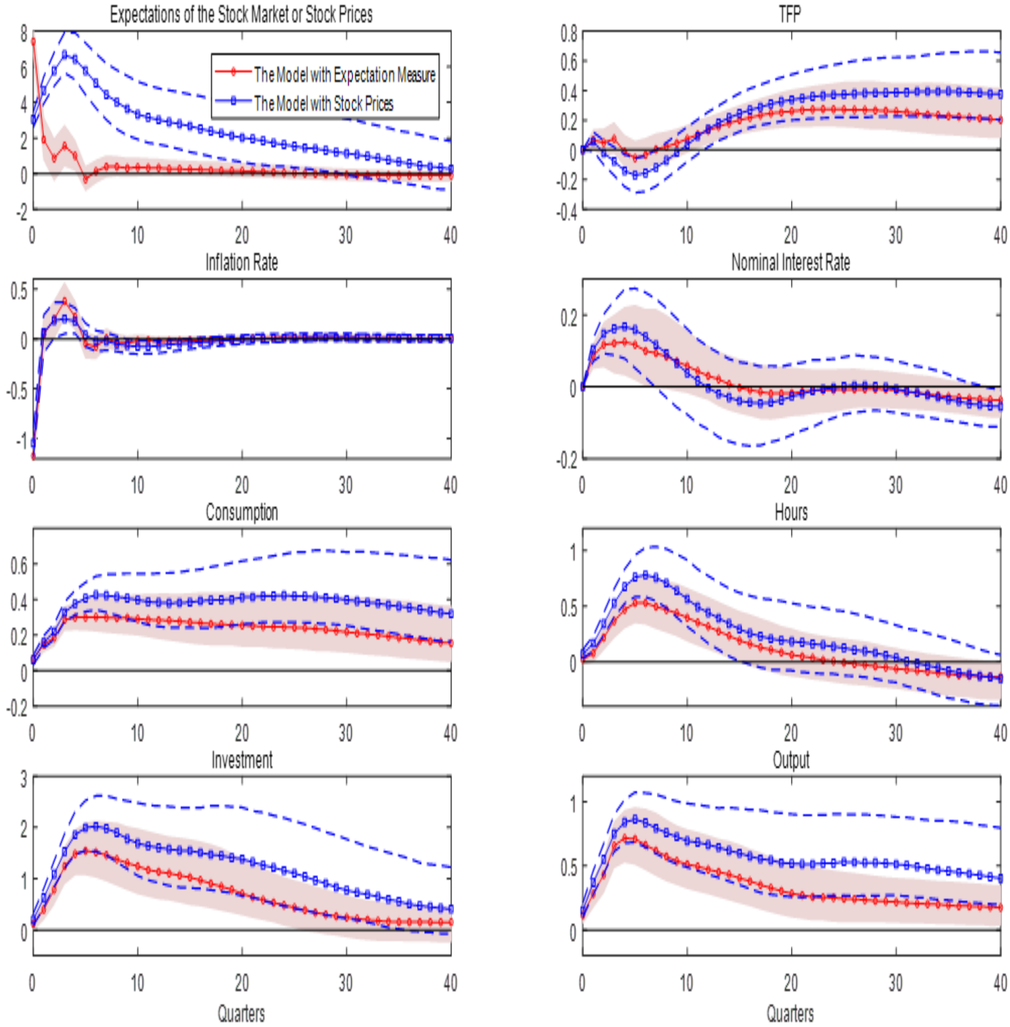
Note: This figure displays the impulse response functions of the baseline model estimated by removing the positive impact restriction on the survey measure of expectations and keeping all other restrictions on TFP, the inflation rate, and the nominal interest rate.

Figure 5: Impulse Response Functions of the Alternative Model with Consumer Confidence



Note: This figure displays the impulse response functions of the model with consumer confidence in place of the measure of investor expectations of future stock market returns. In the this alternative model, news shocks are identified by imposing the positive impact restriction on consumer confidence and keeping all other restrictions on TFP, the inflation rate, and the nominal interest rate. For the purpose of comparison, the figure also reports the IRFs from the baseline model with the measure of investor expectations, which are shown in Figure 2.

Figure 6: Impulse Response Functions of the Alternative Model with Stock Prices



Note: This figure displays the impulse response functions of the model with stock prices in place of the measure of investor expectations of future stock market returns. In the this alternative model, news shocks are identified by imposing the positive impact restriction on stock prices and keeping all other restrictions on TFP, the inflation rate, and the nominal interest rate. For the purpose of comparison, the figure also reports the IRFs from the baseline model with the measure of investor expectations, which are shown in Figure 2.

Table 1: Identification Strategy

Expectations of Future Stock Market Returns	TFP	Inflation Rate	Nominal Interest Rate	Other Variables
(+)	(0)	(−)	(0)	

Note: This table shows the set of our sign and zero restrictions imposed to identify news shocks. (+) and (−) mean imposing the positive and negative sign restrictions on the impact impulse response of a variable, respectively. (0) means imposing the zero restriction on the impact impulse response of a variable, and the blank cell means leaving the impulse response of a variable unrestricted.

Table 2: Forecast Error Variance Decomposition (FEVD) in the Baseline Model

	h=0	h=4	h=8	h=16	h=24	h=40
Investor Expectations	0.52	0.42	0.38	0.35	0.34	0.33
	[0.45,0.60]	[0.35,0.49]	[0.31,0.46]	[0.27,0.43]	[0.26,0.42]	[0.24,0.41]
TFP	0.00	0.02	0.02	0.07	0.13	0.14
	[0.00,0.00]	[0.01,0.05]	[0.01,0.06]	[0.03,0.13]	[0.06,0.22]	[0.07,0.25]
Inflation Rate	0.52	0.41	0.39	0.38	0.37	0.37
	[0.44,0.59]	[0.34,0.48]	[0.33,0.46]	[0.32,0.45]	[0.31,0.44]	[0.30,0.44]
Nominal Interest Rate	0.00	0.04	0.04	0.05	0.05	0.06
	[0.00,0.00]	[0.01,0.09]	[0.01,0.12]	[0.02,0.12]	[0.02,0.12]	[0.02,0.13]
Consumption	0.05	0.32	0.33	0.25	0.22	0.20
	[0.02,0.10]	[0.23,0.44]	[0.21,0.46]	[0.13,0.38]	[0.11,0.35]	[0.10,0.34]
Hours	0.01	0.13	0.18	0.13	0.12	0.12
	[0.00,0.02]	[0.05,0.22]	[0.08,0.30]	[0.06,0.26]	[0.05,0.23]	[0.05,0.23]
Investment	0.01	0.20	0.24	0.21	0.21	0.20
	[0.00,0.04]	[0.11,0.32]	[0.13,0.38]	[0.11,0.36]	[0.11,0.35]	[0.10,0.34]
Output	0.03	0.28	0.32	0.29	0.27	0.25
	[0.01,0.07]	[0.16,0.39]	[0.19,0.46]	[0.17,0.44]	[0.15,0.41]	[0.13,0.38]

Note: This table reports the share of the forecast error variance attributable to news shocks identified from the baseline model. The numbers denote median shares, and the numbers in brackets are 16th and 84th quantiles. The letter h refers to forecast horizon.