NBER WORKING PAPER SERIES

DO MOOD SWINGS DRIVE BUSINESS CYCLES AND IS IT RATIONAL?

Paul Beaudry
Deokwoo Nam
Jian Wang

Working Paper 17651
http://www.nber.org/papers/w17651

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2011

This paper has received indirect support from the SSHRC of Canada and the Fellowship program at the Bank of Canada. All views are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Dallas , the Federal Reserve System, or the National Bureau of Economic Research.

Do Mood Swings Drive Business Cycles and is it Rational?
Paul Beaudry, Deokwoo Nam, and Jian Wang
NBER Working Paper No. 17651
December 2011
JEL No. E1,E2,E32

ABSTRACT

This paper provides new evidence in support of the idea that bouts of optimism and pessimism drive much of US business cycles. In particular, we begin by using sign-restriction based identification schemes to isolate innovations in optimism or pessimism and we document the extent to which such episodes explain macroeconomic fluctuations. We then examine the link between these identified mood shocks and subsequent developments in fundamentals using alternative identification schemes (i.e., variants of the maximum forecast error variance approach). We find that there is a very close link between the two, suggesting that agents' feelings of optimism and pessimism are at least partially rational as total factor productivity (TFP) is observed to rise 8-10 quarters after an initial bout of optimism. While this later finding is consistent with some previous findings in the news shock literature, we cannot rule out that such episodes reflect self-fulfilling beliefs. Overall, we argue that mood swings account for over 50% of business cycle fluctuations in hours and output.

Paul Beaudry
Department of Economics
University of British Columbia
Vancouver, Canada
and University of British Columbia
and also NBER
paulbe@interchange.ubc.ca

Deokwoo Nam
Department of Economics
City University of Hong Kong
83 Tat Chee Avenue, Kowloon, Hong Kong
deokwnam@cityu.edu.hk

Jian Wang
Research Department
Federal Reserve Bank of Dallas
2200 N. Pearl St.
Dallas, TX 75201
Jian.Wang@dal.frb.org

1 Introduction

There is a long tradition in macroeconomics suggesting that business cycles may be primarily driven by bouts of optimism and pessimism. Keynes' well-known "animal spirits" comment is one expression of this view. However, within this tradition, there is considerable disagreement with respect to the sources of such changes in sentiment. At one extreme, there is the view that such mood swings are entirely rational because of a self-fulfilling feedback loop. According to this perspective, optimism causes an increase in economic activity which precisely validates the original optimistic sentiment.[1] Closely related to this view, because of its shared rational basis, is the news view of mood swings.[2] In this view, optimism arises when agents learn about forces that will positively affect future fundamentals, so bouts of optimism precede positive changes in fundamentals but do not cause them. Finally, there is a third view suggesting that macroeconomic mood swings are only driven by psychological factors and therefore are not directly related to future developments of fundamentals.[3]

The aim of this paper is to contribute to the above debate regarding the source and nature of business cycles by approaching the issue on two different fronts.[4] As a first step, we will provide new evidence on the relevance of optimism and pessimism as the main driver of macroeconomic fluctuations. We pursue this goal by exploiting the sign restrictions method proposed by Uhlig (2005) and Mountford and Uhlig (2009) to isolate optimism shocks in vector autoregression (VAR) setups. In a second step, we examine if such optimism-driven fluctuations are related to subsequent changes in fundamentals. To proceed, we will isolate shocks to future total factor productivity (TFP) growth by using the maximum forecast error variance method proposed by Francis et al. (2005) and a closely related method proposed by Barsky and Sims (2011). We then compare the shocks to future TFP growth with our identified optimism shocks. There are four different conclusions that can arise from our exploration. We could find that optimism-driven fluctuations are important or unimportant for understanding business cycles; and we could observe that such fluctuations are related or not to future changes in productivity. Whatever the outcome, our results should help answer the questions posed in the title of this paper as we will interpret mood swings as having at least some rational underpinning if they are related to subsequent changes in fundamentals.

The first section of the paper will therefore begin by examining the relevance of optimism and pessimism

[1]See for example Benhabib and Farmer (1994) and Farmer and Guo (1994).

[2]See for example Cochrane (1994a and 1994b), Beaudry and Portier (2004 and 2006), Jaimovich and Rebelo (2009), and Schmitt-Grohe and Uribe (2009).

[3]See for example the book by Akerlof and Shiller (2009).

[4]Although there has been considerable empirical research on the role of beliefs, news and animal spirits in business cycles fluctuations, there remains considerable disagreement about the results. For example, regarding the importance of news shock, Barsky and Sims (2011 and forthcoming) arrive at substantial different conclusions to those of Beaudry and Portier (2006) and Beaudry and Lucke (2010). One of our objectives is to clarify the source of these differences and to provide new evidence.

in business cycle fluctuations by exploiting sign-restriction based identification strategies. Sign restrictions have been proposed, and used quite extensively in the recent structural VAR literature. They serve as an alternative to conventional "zero restrictions" to identify structural shocks and their associated impulse response functions.[5] This literature argues that sign restrictions can be derived more easily from theory than zero restrictions, which makes the sign restrictions approach more attractive and credible.

Our approach will exploit different sets of sign restrictions to identify what we refer to as optimism shocks. In the most constraining case, we impose 4 sign restrictions. Our idea is to isolate movements of optimism which are neither driven by improvements in current technology nor expansionary monetary policy. Accordingly, in our most restrictive case, we define an optimism shock as a shock that is associated with increases in stock prices and consumption. At the same time, the shock is not associated with a decrease in interest rates nor any movement in measured TFP. We document extensively the robustness of this identification scheme to reducing the set of sign restrictions and to changing the size of the system in which we impose these restrictions. For example, we consider cases where we impose only 1, 2 or 3 of these four sign restrictions, and cases where the VAR includes 5 to 8 variables. Moreover, we examine the stability of our results over subsamples. While our work mainly uses information on standard aggregate variables – such as stock prices and consumption – to help identify bouts of optimism, we also report results when we include survey measures of consumer confidence in our VARs. The results from these exercises are very homogeneous as long as we maintain the assumption that optimism is associated with an increase in stock prices. We find that our identified optimism shock is associated with standard business cycle type phenomena in the sense that it generates a simultaneous boom in output, investment, consumption, and hours, with consumption leading the cycle. Moreover, we find that such optimism shocks generally accounts for over 50% of the forecast error variance of hours at business cycle frequencies. So the sign restrictions approach suggests that bouts of optimism and pessimism are, as the business press would suggest, a very important component in business cycle fluctuations.

Our use of sign restrictions to identify optimism shocks only imposes restrictions in the short run, which allows us to see if such shocks are associated with subsequent movements in fundamentals. While optimism could be associated with eventual developments in different fundamentals, we restrict our attention here to movements in TFP as is common in the news shock literature. We find that our identified optimism shocks are followed by an eventual increase in measured TFP, but this increase does not manifest itself for at least two to three years after the initial bout of optimism. These findings echo the results in Beaudry and Portier (2006) which examine the effects of shocks to stock prices on subsequent TFP growth in a bi-variate system.

[5] For example, see Dedola and Neri (2007), Peersman and Straub (2009), and Enders, Muller, and Scholl (2011).

Although we find that optimism shocks are associated with subsequent movements in TFP, this does not tell us if most or much of the predictable growth in TFP is proceeded by the economic expansion linked to initial bouts of optimism. In particular, Barsky and Sims (2011) have argued to the contrary that much of the predictable growth in TFP is not preceded by a boom period (which conflicts with Beaudry and Portier's results). For this reason, we want to separately identify shocks to optimism and shocks that predict future TFP growth and see how they are related.

In the second part of the paper, we turn to systematically exploring the link between predictable movements in TFP and the bouts of optimism we identified using sign restrictions. To examine this issue, we begin by isolating shocks that can be associated with predictable movements in TFP. We use two different (but closely related) identification schemes to isolate such shocks. In particular, we use a variant of the maximum forecast error variance method introduced by Francis et al. (2005) and the method proposed by Barsky and Sims (2011). The maximum forecast error variance method of Francis et al. was developed as an alternative to using standard long-run restrictions – as for example used in Blanchard and Quah (1989) or Gali (1999) – to identify technology shocks. The method aims to isolate shocks that maximize the forecast error variance of a variable attributable to those shocks at a long but finite forecast horizon. In our case, we will be looking for a shock that both maximizes its contribution to the forecast error variance of TFP at a given horizon and initially has no impact on TFP. We will refer to such a shock as a shock to future TFP. This method is very similar to the method proposed by Barsky and Sims. However, the shock isolated by Barsky and Sims' method maximizes its contribution to the forecast error variance of TFP not only at a given horizon but also at all horizons up to a truncation horizon. Hence, these two methods differ in their treatments of short-run/temporary movements in TFP. Our application of the method of Francis et al. is aimed at isolating shocks that have a permanent effect on TFP, while Barsky and Sims' method may confound shocks that have either permanent or temporary effects on TFP.

When using the methods of Francis et al. and Barsky and Sims to identify future TFP growth shocks, we find somewhat different results depending on the forecast horizon used in these methods. In the case of Francis et al.'s method, the results are very similar regardless of the forecast horizons used. The identified future TFP shocks are almost perfectly correlated with the optimism shocks identified from the sign restrictions method. The identified future TFP shocks and optimism shocks generate very similar impulse responses. These results suggest an amazing degree of coherence between the identified optimism shocks and the identified future TFP growth shocks.[6] In the case of Barsky and Sims' method, the results are sensitive to the choice

[6] The approach adopted here of comparing shocks derived from short-run sign-restriction based identification schemes with shocks derived from long-run type forecast-error-variance identification schemes is similar in spirit to the exercises performed in Beaudry and Portier (2006) with their bi-variate system. The advantage of the current approach which exploits sign restrictions

of forecast horizons. If we use a long forecast horizon (80 or 120 quarters), we get very similar results to those found in using Francis et al.'s method. This finding further suggests that optimism shocks and future TFP growth shocks may be closely related. However, if we use a shorter horizon, for example 40 quarters,[7] we get a substantially different picture. In this later case, the impulse responses to the predictable TFP growth shocks are quite different from those to the optimism shocks. For example, the future TFP growth shocks are associated with an initial decline in hours worked and investment, while this is not the case for the optimism shocks identified from sign restrictions or for the future TFP growth shocks identified from Francis et al.'s method. As we discuss later, this discrepancy may result from different treatments of temporary but predictable components in TFP in these identification methods.

In total, we believe that our results overwhelmingly suggest that answers to the questions posed in the title are: yes, mood swings are very important in business cycle fluctuations; yes, they are likely to have some grounding in rationality as they appear to be strongly associated with long-run movements in TFP. However, these results do not tell us if the mood swings are a reflection of the future growth (as suggested by the news shock literature) or cause the future growth (as suggested by the self-fulfilling equilibrium literature), as the methods used in this paper cannot separate these two. Moreover, the results do not tell us if the size of the initial macroeconomic responses is quantitatively reasonable given the long term movements in TFP.

As a final way to show how important optimism and pessimism may be in driving business cycles, we examine the property of a shock that explains most of the forecast error variance of hours at business cycle frequencies. This exercise is very close to that undertaken in Uhlig (2003) for GDP. While there is no clear reason to believe that the shock maximizing its contribution to the forecast error variance of hours at business cycle frequency has a structural interpretation, it is astonishing to see how closely it mimics our optimism shock and our future TFP growth shock. We believe that this additional finding provides further support to the notion that rationally grounded mood swings may likely be the primary driver of macroeconomic fluctuations.

On most dimensions, business cycle fluctuations which we identify as being associated with bouts of optimism have quite intuitive properties and generally conform to the conventional narrative of a boom. These identified fluctuations correspond to simultaneous expansions in consumption, investment and hours worked with consumption leading the other two. Moreover, they are associated with a gradual but persistent increase in real wages, and a mild increase in real interest rates. The two areas where our identified optimism

and maximum forecast error variance methods is that it can be easily implemented on VARs of different sizes. In contrast, the zero-restriction based approach in Beaudry and Portier is difficult to implement beyond a bi-variate system and has been criticized for this reason.

[7]Barsky and Sims (2011) use a horizon of 40 quarters in their study.

shocks induce dynamics that are somewhat different from standard accounts of fluctuations are with respect to TFP movements and movements in inflation. As we have already emphasized, for most of the expansion period, we do not observe any increase in TFP (once the measure is corrected for variable capacity utilization). In addition, the induced expansions do not appear associated with inflation. This later fact creates an interesting challenge to conventional business cycle analysis, as an expansion is generally perceived as either driven by an increase in the production capacity of the economy or alternatively it should be putting upward pressure on inflation. Our optimism shocks appear to cause booms with neither TFP nor inflation rising for an extended period of time.

The objectives and analysis of this paper are closely related to those found in Barsky and Sims (2011 and forthcoming). However, we will argue that our results paint a very different picture of business cycles; one that is more in line with a typical business press narrative of macroeconomic fluctuations, but is also much more difficult to explain given standard theories. In particular, our results suggest that expansions are characterized by initial periods of 2 to 3 years in which agents appear optimistic about the future but there is no simultaneous growth in TFP (or inflation). In this sense, the evidence we present suggests that it is bouts of optimism or pessimism themselves that drive the bulk of macroeconomic fluctuations rather than a subsequent rise in productivity. Although Barsky and Sims' analysis suggests that agents' advance knowledge of future productivity growth (news) may be important in understanding macroeconomic fluctuations – which is consistent with our findings – their results suggest that optimism (or confidence) itself does not generate expansions, as they argue that an expansion only arises when productivity starts growing not when it is simply anticipated to grow. Moreover, they find that the lag between bouts of optimism (or confidence) about the future and subsequent TFP growth is only about one quarter. Accordingly, their analysis downplays the role of the mood in driving fluctuations but instead explains fluctuations by essentially the same mechanisms emphasized in the real business cycle (RBC) literature. That is, it is a contemporaneous increase in productivity which causes booms. Since the results of this paper and those of Barsky and Sims (2011 and forthcoming) are in conflict, we highlight the source and potential explanations of these differences in the paper.

The remainder of the paper is arranged as follows. Section 2 describes the sign restrictions method and presents implications of optimism shocks this method identifies. Section 3 reports results of shocks identified from the maximum forecast error variance method, which we use to identify shocks to future TFP growth. In Section 4, we compare the two sets of shocks and discuss the relationship between our results and others found in the literature. Section 5 concludes and discusses directions for future research.

2 Identifying Optimism Shocks

In this section, we first briefly introduce the sign restrictions method that we use to identify optimism shocks. Then we describe the data and three different sets of sign restrictions imposed on the data to identify optimism shocks. Finally, we present our empirical results.

2.1 Sign Restrictions Method

The sign restrictions method has been widely used in the recent SVAR literature. The basic idea of this method is to impose sign restrictions on the impulse responses of a set of variables as a means of recovering a structural shock of interest. For example, according to the conventional wisdom and many theoretical models, a contractionary monetary shock should raise the interest rate and lower output and prices in the short run. So the sign restrictions method would suggest that monetary shocks are identified by imposing such restrictions on the impulse responses of a set of variables in the data. That is, this identification scheme recovers shocks which have a set of pre-specified qualitative features.

To discuss the sign restrictions method, let us start from the following reduced-form VAR model:

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

where Y_t is an $n \times 1$ vector of variables in levels, Φ_k is reduced-form VAR coefficient matrix, and u_t is reduced-form innovations with the variance-covariance matrix Σ_u. The reduced-form moving-average representation is expressed as:

$$Y_t = \mu + \sum_{h=0}^{\infty} B\left(h\right) u_{t-h}, \tag{1}$$

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

$$u_t = A_0 \epsilon_t, \tag{2}$$

where variances of structural shocks are normalized to be equal to one (i.e., $E\left[\epsilon_t \epsilon_t'\right] = I$) and the impact matrix A_0 satisfies $A_0 A_0' = \Sigma_u$. Alternatively, we can rewrite A_0 as follows:

$$A_0 = \widetilde{A}_0 Q, \tag{3}$$

where $\widetilde{A}_0$ is any arbitrary orthogonalization of Σ_u (e.g., Cholesky decomposition of Σ_u) and Q is an orthonormal matrix (i.e., $QQ' = I$). The identification of 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.

Equations (1), (2), and (3) imply that the structural moving-average representation can be written as:

$$Y_t = \sum_{h=0}^{\infty} R(h)\, \epsilon_{t-h}, \tag{4}$$

where $R(h) = C(h)\, Q$ with $C(h) = B(h)\, \widetilde{A}_0$. So 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 $R(h)$ denoted by $r^{(j)}(h)$:

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

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 $r^{(j)}(h)$ denoted by $r_i^{(j)}(h)$:

$$r_i^{(j)}(h) = C_i(h)\, q^{(j)}, \tag{5}$$

where $C_i(h)$ is the i^{th} row of $C(h)$. In what follows, index j for a structural shock of interest is dropped when it raises no confusion.

A structural shock of interest is identified by imposing sign restrictions on impulse responses of selected variables to this shock $r_i(h)$ for some horizons $h = \underline{h}_i, \cdots, \overline{h}_i$, following the shock. It follows from equation (5) that this is equivalent to identifying the unit vector q that satisfies the imposed sign restrictions as much as possible. In particular, we take the penalty-function approach proposed in 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 impact restrictions in addition to sign restrictions.

Following Mountford and Uhlig (2009), we impose sign restrictions by solving the following minimization problem:

$$q^* = \arg\min_q \Psi(q) \;\; s.t. \; q'q = 1, \tag{6}$$

where the criterion function $\Psi(q)$ is given by:

$$\Psi(q) = \sum_{i \in I_{S_+}} \sum_{h=\underline{h}_i}^{\overline{h}_i} f\left(-\frac{C_i(h)\, q}{\sigma_i}\right) + \sum_{i \in I_{S_-}} \sum_{h=\underline{h}_i}^{\overline{h}_i} f\left(\frac{C_i(h)\, q}{\sigma_i}\right),$$

where I_{S_+} (I_{S_-}) is the index set of variables whose impulse responses $C_i(h)q$ are restricted to be positive (negative) from horizon $\underline{h}_i$ to horizon $\overline{h}_i$ following a structural shock of interest (e.g., an optimism shock in our study). σ_i is the standard error of variable i and the impulse response is re-scaled by σ_i to make it comparable across different variables. The penalty function f on the real line is defined as $f(x) = 100x$ if $x \geq 0$ and $f(x) = x$ if $x < 0$. Computationally, we solve this minimization problem by using simplex and generic algorithms that are available on Matlab.

In our application, in addition to a set of sign restrictions on the impulse responses to an optimism shock, we also want to distinguish optimism shocks from contemporaneous TFP shocks. This corresponds to imposing a zero impact restriction on the impulse response of TFP following an optimism shock. In the penalty-function approach, such zero impact restriction can be easily incorporated.[8] Without loss of generality, let TFP be the first element of Y_t. Then the zero restriction on the impact impulse response of TFP can be written as a restriction on the unit vector q:

$$R_{zero}q = 0,$$

where R_{zero} is the first row of $C(0)$ (i.e., $R_{zero} = C_1(0)$). In this case, we replace the minimization problem in equation (6) with:

$$q^* = \arg\min_q \Psi(q) \;\; s.t. \;\; (1) \;\; q'q = 1; \;\; (2) \;\; R_{zero}q = 0. \tag{7}$$

For the actual estimation, we employ a Bayesian approach. Specifically, we use a flat Normal-Wishart prior (see Uhlig (2005) for detailed discussion on the properties of Normal-Wishart prior), while the numerical implementation employs the sterographic projection. This can be summarized as follows. First, we take a draw from the Normal-Wishart posterior for (Φ, Σ_u) which is parameterized by their OLS estimates. Next, for a given draw, we solve the numerical minimization problem in equation (7) using simplex and generic algorithms. When we solve the numerical minimization problem, we obtain the unit vector q as a candidate for q^* in equation (7) by applying the stereographic projection inversely.[9] Then, statistical inferences (e.g., confidence intervals of impulse responses) are based on the distribution of those draws that solve equation (7).

[8] In general, the method can also be modified to impose the restriction that the impulse response of a variable is zero for multiple horizons.

[9] The stereographic projection is a mapping that projects the unit sphere onto the plane. Thus, a unit vector q (i.e., a point on the unit sphere) can be obtained by applying the stereographic projection inversely. That is, we first draw an arbitrary $(n-1) \times 1$ vector, denoted by γ, on the plane, and then project γ on the unit sphere to obtain an $n \times 1$ unit vector q that also satisfies the zero restriction in equation (7).

2.2 Data and Imposed Sign Restrictions

In our empirical studies, we use quarterly US data from the sample period 1955Q1 to 2010Q4. The starting and ending dates of our sample are dictated by the availability of the data.[10] Our dataset contains the following variables: TFP, stock price, consumption, investment, output, hours worked, the real interest rate, the inflation rate, the relative price of investment, the real wage, and consumer confidence.

Our main measure of TFP is the factor-utilization-adjusted TFP series first developed by Basu, Fernald, and Kimball (2006) and updated on John Fernald's website.[11] We also report some results using a non-capacity-utilization-adjusted TFP series to illustrate the difference (the series is also taken from John Fernald's website). In general, we believe that the adjusted series is a much better indicator of technological progress and we therefore take it as our baseline series for TFP.[12]

Our stock price measure is the end-of-period Standard and Poor's 500 composite index (obtained from the *Wall Street Journal*) divided by the CPI (CPI of all items for all urban consumers from the Bureau of Labor Statistics (BLS)). 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 hours of all persons in the non-farm business sector obtained from the BLS. These five variables, stock price, consumption, investment, output, and hours worked, are transformed in per capita terms by dividing each of them by the civilian noninstitutional population of 16 years and over from the BLS. The real interest rate is the effective federal funds rate (from the Federal Reserve Board) minus the inflation rate which is measured by the annualized quarterly CPI growth rate. The relative price of investment is calculated as the ratio of the PPI index for capital equipment to the PPI index for consumption good. Both indices are from the BLS. The real wage is measured by non-farm business hourly compensation from the BLS divided by the GDP deflator from the BEA. Following Barsky and Sims (2011), we use the question in Table 16 of the Survey of Consumers by the University of Michigan as a measure of consumer confidence. Column "Relative" in Table 16 of the survey summarizes responses to the 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

[10] The federal funds rate that is used to calculate the real interest rate starts in 1955Q1. The factor-utilization-adjusted TFP series ends in 2010Q4. The results reported in this paper are robust to the sample period from 1955Q1 to 2007Q4, which excludes the recent global financial crisis.

[11] Our (adjusted and non-adjusted) TFP series are obtained from the website of John Fernald. Note that these series are updated in June 2011 by Fernald. We also use adjusted TFP in Beaudry and Lucke (2010) as a robustness check. Our main findings reported through this paper hold up well with this alternative measure of adjusted TFP.

[12] Jaimovich and Rebelo (2009) and Nam and Wang (2010a) show, in a model with variable capital utilization, that one should use utilization-adjusted TFP when trying to identify news shocks – which is one interpretation of the optimism shocks we examine here.

unemployment or depression, or what?" We use E5Y to denote this measure of consumer confidence.

In our benchmark VAR model, Y_t contains five variables ($n = 5$): TFP, stock price, consumption, the real interest rate, and hours worked. All variables are logged except for the real interest rate and enter the system in levels.[13] A constant and four lags ($p = 4$) are also included in our benchmark and all other systems. Our results do not change qualitatively when different numbers of lags are used.

We use three different sets of sign restrictions to identify optimism shocks as summarized in Table 1. Our idea is that optimism should be associated with increases in stock prices and consumption as these are generally viewed as the best indicators of how individuals perceive the future. We pursue three identification schemes to explore the robustness of this idea. Alternatively, we could use survey measures of consumer confidence to help identify optimism shocks. While we will report results which include a measure of consumer confidence, we believe that such measures are inferior to stock prices and actual consumer spending in picking up broad based sentiments.

In all three identification schemes, we impose the zero restriction that the optimism shock be orthogonal on impact to changes in TFP as to differentiate optimism shocks from current improvements in technological opportunities. This type of restrictions has been used in the news shock literature (see for example Beaudry and Portier (2006), Beaudry and Lucke (2010) and Barsky and Sims (2011)), and we maintain it here since one form of optimism shocks may be news shocks. The three sets of sign restrictions we use will be referred to as: Identifications I, II, and III. Identification I only imposes one sign restriction (in addition to the zero restriction on TFP) that the impulse response of stock price should be positive on impact. For all results presented in this paper, the sign restrictions are imposed for just one period. Identification I is a quite minimal set of restrictions and may be seen as insufficient to identify optimism shocks, since other shocks besides TFP or optimism shocks may also affect stock prices. The attractive feature of Identification I is that it gives the data the greatest freedom of speaking for itself. Note that the sign restrictions of Identification I is quite similar in spirit to the short-run restriction used in Beaudry and Portier (2006) to identify news shocks. Their study involves a bi-variate system, where they identify the news shock as a positive shock to stock price which is orthogonal to current TFP. Identification I can be seen as a generalization of this idea which can be implemented in systems of any size. Building upon Identification I, Identification II goes one step further and restricts the impulse response of consumption to also be positive on impact in response to an optimism shock. This restriction follows for example Cochrane's (1994b) argument that agents may have advance information about future economic conditions that they use when making consumption decisions.

[13] We also consider similar VAR systems in which hours worked is replaced with investment or output, or consumption is replaced with investment. Our findings remain qualitatively unchanged in these cases. Results are available upon request.

The sign restrictions in Identifications I and II might still be viewed as insufficient to isolate optimism shocks, as monetary shocks may also satisfy these sign restrictions. In many models, an expansionary monetary shock could induce a rise in stock price and consumption, but no immediate effect on TFP. For this reason, we consider identification III where in addition to the restrictions inherent to Identification II, we impose the restriction that the impulse response of the real interest rate be non-negative on impact following an optimism shock. Identification III is our most constraining identification scheme. One interesting aspect to examine is how impulse responses change as we go from our least restrictive scheme to our most restrictive scheme. If there are many important shocks that share some of the same sign properties, then we should expect the impulse responses change substantially across our identification schemes. In contrast, if the optimism shock is a very dominant one, then the three schemes may give similar results.

We also consider larger VAR systems than our benchmark five-variable system. In all larger systems, we still use the same sets of sign restrictions as in the five-variable systems, thereby leaving the impulse responses of newly added variables unrestricted.

2.3 Results of the Sign Restrictions Method

2.3.1 Results in the Benchmark Five-variable System

Figure 1 displays the impulse responses to a unit identified optimism shock in our benchmark five-variable system. Each panel of the figure corresponds to one of three identification strategies described in Table 1.

Under Identification I, which corresponds to the first panel, we see that stock prices rise on impact and TFP does not change. This is by construction as they are the identifying restrictions. Interestingly, consumption and the real interest rate also rise immediately following the identified shock with consumption continuing to rise to a permanently higher level, suggesting that we may be isolating an optimism shock. Hours worked barely change on impact but increase gradually over time. They exhibit a hump-shaped response before converging back to the initial level. Note that hours and consumption rise substantially above zero and reach their peaks before TFP starts to rise above zero. An important aspect to notice in this panel is that TFP eventually rises to a higher long-run level, though it does not rise significantly above zero until about ten quarters following the identified optimism shock. This finding has two interesting implications. First, it suggests that the initial increase in optimism either anticipates the eventual rise in TFP or causes it. Second, it suggests that bouts of optimism may at least in part be grounded in rational calculations as they appear to anticipate changes in fundamentals. These findings are very similar to Beaudry and Portier (2006), suggesting that innovations in stock prices that are orthogonal to TFP induce a generalized boom of the economy which precedes an eventual rise in TFP.

In the next two panels of Figure 1, we can see that the above results are robust to adding sign restrictions on consumption and the real interest rate sequentially as implied by Identifications II and III. The main difference in terms of impulse responses between Identifications I and II is not only that consumption increases more on impact (which is by construction), but also that it settles at a higher new long-run level. Hours also reach a higher peak and TFP converges to a higher long-run level in Identification II when compared to Identification I. In Identification III, we further restrict the impulse response of the real interest rate to be positive on impact of an optimism shock. This restriction helps assure that our identified optimism shock is not capturing an expansionary monetary shock. Except for the real interest rate, the impulse responses of other variables are almost identical in Identifications II and III, suggesting that our main findings are unlikely to be driven by expansionary monetary shocks.[14] However, imposing the positive impulse response of the real interest rate on impact does make hours less amplified in the medium run. This is also what is observed on investment and output in larger systems that we will consider in the next section.

Figure 2 presents the impulse responses of the alternative five-variable system in which non-adjusted TFP is used as the first variable. Overall, the impulse responses are similar to those in the benchmark five-variable system with the exception of the first variable. When non-adjusted TFP is used as a measure of true technology, the impulse response of TFP looks very different in particular for the first ten quarters. In this case, TFP rises immediately and stays above zero for the first ten quarters. The immediate rise of non-adjusted TFP following an optimism shock can be seen as mainly reflecting an increase in the factor utilization rate. As transitory fluctuations in the utilization rate die out over time, TFP declines back to zero before it eventually rises to a permanently higher level. The period between the arrival of optimism and the eventual permanent rise of TFP is about ten quarters no matter if we use adjusted or non-adjusted TFP.[15] Our results show that the sign restrictions method is robust to different measures of TFP when estimating the potential link between optimism and future rises in TFP. Since the measurement of TFP is subject to many errors, being robust to different measures is an important advantage.

There is another noticeable change when non-adjusted TFP is used: the permanent effect of the optimism shock on stock price and consumption seems quite weak under Identification I. Both stock price and consumption converge back to a level close to zero at horizon 40 quarters. However, the positive sign

[14] In an exercise that is not reported in this paper, we also identify both monetary and optimism shocks sequentially to make sure that our identified optimism shock does not pick up the effect of an expansionary monetary shock. Our main findings hold up qualitatively well in this case. Results are available upon request.

[15] Nam and Wang (2010a) show in a two-country dynamic stochastic general equilibrium model that the anticipation horizon of news-based optimism shocks is critical for the response of the real exchange rate to such shocks. When the anticipation horizon is long (about eight quarters or more), the real exchange rate appreciates following a positive optimism shock, while it depreciates when the anticipation horizon is short.

restriction on the impulse response of consumption alleviates this problem. Stock price and consumption settle at higher new long-run levels under Identifications II and III than under Identification I. That is, the positive restriction on the impulse response of consumption appears to help capture the permanent effect of optimism shocks when TFP is not adjusted for utilization.

Table 2 reports the share of the forecast error variance (FEV) of each variable that is attributable to optimism shocks in the five-variable system. Panels A and B report the results under all three sets of sign restrictions when utilization-adjusted TFP and non-adjusted TFP are used, respectively. Consistent with the results of the impulse responses, optimism shocks are found to play an important role in driving aggregate macroeconomic fluctuations at business cycle frequencies. For instance, under Identification II, optimism shocks account for more than 70% of the FEV of consumption and more than 50% of the FEV of hours at horizons 8 to 40 quarters when adjusted TFP is used. Under all three identification schemes, around 20% of the FEV of TFP at horizon 40 is explained by optimism shocks when either adjusted or non-adjusted TFP is used. Consistent with impulse responses, optimism shocks are found to explain a larger fraction of the FEV of TFP at short horizons when non-adjusted TFP is used than when adjusted TFP is used. For instance, optimism shocks explain 13% of TFP at horizon 4 under Identification III when non-adjusted TFP is used. It is only 1% when adjusted TFP is used.

2.3.2 Results in Larger Systems

Next, we consider larger systems but still use the same sets of sign restrictions described in Table 1. We add investment and output to our benchmark five-variable system. In this seven-variable system, the impulse responses of investment, hours, and output are unrestricted because the impact responses of these three variables to an optimism shock remain controversial in both theoretical and empirical studies.

Figure 3 presents the impulse responses in the seven-variable system.[16] Also presented is the implied impulse response for labor productivity, which we calculated from the impulse responses of output and hours worked. From this figure, it can be seen that our findings from the five-variable system are robust in this seven-variable system. Under all three sets of sign restrictions, stock price, consumption, and the real interest rate jump above zero immediately following a positive optimism shock. TFP does not rise significantly above zero until about ten quarters following a favorable optimism shock. Consumption continues to increase before settling at a higher long-run level. Hours, investment, and output barely move on impact of the optimism shock, but increase substantially above zero before TFP starts to rise. These three variables also exhibit hump-shaped responses: investment and output eventually converge to their new long-run levels while hours

[16]Our findings also hold up well when non-adjusted TFP is used.

revert to the initial level. Labor productivity seems to linger at a constant level until ten quarters, when it starts to rise permanently at the same time when TFP starts to rise significantly above zero.

We check the robustness of our findings in different subsample periods. Figure 4 displays the impulse responses in two subsamples as well as in the full sample when optimism shocks are identified with Identification III. Results are qualitatively similar when the other two identification strategies used in Table 1 are employed. The pre-1978 subsample covers the period from 1955Q1 to 1978Q4 (in the left panel). The post-1983 subsample covers the period from 1983Q1 to 2010Q4 (in the middle panel). The full sample ranges from 1955Q1 to 2010Q4 (in the right panel). We exclude the sample period from 1979Q1 to 1982Q4 when studying subsamples following Dedola and Neri (2007). Dedola and Neri find that the non-borrowed targeting regime adopted by the Federal Reserve during this period induced significant increases in the volatility of the federal funds rate (see Bernanke and Mihov, 1998). In addition, the post-1983 subsample corresponds in part to the Great Moderation period found in US data. We want to check if optimism shocks became more important during this period as argued by Jaimovich and Rebelo (2009).

Figure 4 indicates that our main findings in the full sample hold up well in two important subsamples, the post-1983 subsample and the pre-1978 subsample. We find that macroeconomic variables generally respond more strongly to optimism shocks in the post-1983 subsample than in the pre-1978 subsample. Optimism shocks seem to have larger permanent effects on variables such as TFP, consumption, investment, and output in the more recent subsample. These findings suggest that optimism shocks may have become more important in driving macroeconomic variables in the more recent period. This is consistent with Jaimovich and Rebelo's (2009) argument that expectations may have become more important in driving US economic fluctuations after the mid 1980s after inflation came under control.

In Figure 5, we remove the zero restriction on the impact impulse response of TFP to the optimism shock. We use this exercise to check how much such zero restriction affects our finding that TFP remains close to zero for about ten quarters following a positive optimism shock. The lines with blue circles represent the median responses and the gray areas cover 16th and 84th quantiles. For the purpose of comparison, we also include the median responses when the zero restriction on TFP is imposed (lines with red crosses). Removing the zero restriction on TFP does not change our results significantly. The only noticeable change is that TFP under Identifications II and III displays a slightly greater increase in the first few periods following the shock as compared to the case with the zero restriction on TFP.

Figure 6 displays impulse responses in four eight-variable systems. Each of them is obtained by adding another variable of interest to our above seven-variable system. The impulse response of the newly added variable is unrestricted. The first aspect to note is that the addition of a new variable does not change any of the findings from the seven-variable system. Therefore, we can focus exclusively on the properties of the added variable. In the first panel, we add the inflation rate to the seven-variable system and the optimism shock is identified using Identification II. We use identification II since the real interest rate includes inflation and we do not want to implicitly restrict the behavior of inflation by imposing a restriction on the real interest rate. The interesting finding from this panel is that inflation almost does not change in response to our identified optimism shock. In the second panel, the relative price of investment is added to the seven-variable system. The optimism shock is now identified by the sign restrictions of Identification III of Table 1 (using Identification II produces similar results). Following a positive optimism shock, we see that the relative price of investment (measured by the PPI of capital equipments divided by the PPI for consumption goods) increases on impact, but eventually declines when TFP increases (about ten quarters after the impact of a favorable optimism shock). This suggests that our optimism shock is not capturing a surprise change in the relative capacity of the economy to produce investment goods relative to consumption goods.

While we believe that stock price and consumption are the best indicators of confidence and changes in agents' expectations about future economic conditions, there are surveys that provide alternative measures of consumer confidence or sentiment on future economic conditions. Despite various data issues related to such survey data, we add a survey measure of consumer confidence to our seven-variable system to examine whether our optimism shocks are also reflected in such surveys. The third panel of Figure 6 shows the impulse responses to a positive optimism shock under Identification III when we add a measure of 5-year expectations of consumers from the Survey of Consumers of the University of Michigan (denoted by E5Y). The panel indicates that following an identified optimism shock, this measure of consumer confidence rises strongly on impact and exhibits a persistent decline over time. In addition, we find that optimism shocks account for a large fraction of the forecast error variance of E5Y.[17] This finding is consistent with Barsky and Sims (2011), suggesting that this measure of consumer confidence is closely related to our notion of optimism.

In the last panel of Figure 6, the real wage is added to the seven-variable system. Following a positive optimism shock (using Identification III), the real wage increases gradually and converges to a permanently higher level. This finding suggests that the identified optimism shock is not likely to result from a positive labor supply shock, which could have been one alternative interpretation of our identified optimism shock.

Table 3 displays results of the forecast error variance decomposition for the seven-variable system. For

[17] To save space, the results of the forecast error variance decomposition for eight-variable systems are not reported. Results are available upon request.

brevity, we only report results for the case of utilization-adjusted TFP. We confirm in this larger system that optimism shocks remain important in driving business cycle fluctuations of macroeconomic variables. For instance, under Identification II, optimism shocks account for around 50% of the FEV of hours and investment and more than 50% of the FEV of output at horizons of 8 to 40 quarters. Moreover, optimism shocks account for more than 40% of the FEV of stock price at very short horizons. This result is consistent with previous findings that short-run movements of asset prices may be driven by changes in expectations about future fundamentals rather than current fundamentals (for instance, see Engel and West (2005) and Nam and Wang (2010b)). The share of the FEV of the real interest rate attributable to optimism shocks is relatively small unless we impose the sign restriction on the real interest rate.

3 Identifying Future TFP Growth Shocks

In this section, we first briefly introduce two methods used to identify what we will call future TFP growth shocks. Then we implement these methods in the five- and seven-variable systems studied previously and examine how the resulting shocks compare with the optimism shocks we identified using sign restrictions. Our goal is to examine the extent to which optimism shocks and future TFP shocks are related. Given that our identified optimism shocks were observed to precede future TFP growth, we know that there is at least some link between optimism and future TFP. In this section, we want to examine the link more thoroughly and explain potential conflicting results observed in the data. In particular, the results of Beaudry and Portier (2006) suggest that the two notions may be closely related, while the results of Barsky and Sims (2011) suggest that the link is not very tight.

The first method we use to isolate future TFP (growth) shocks is the maximum forecast error variance share method (or the max share method) introduced in Francis et al. (2005). They initially propose this method as an alternative to conventional long-run restrictions to identify technology shocks (see Gali (1999) among others). In this paper, we explore an application of this method to identify future TFP shocks. The second alternative method is that proposed in Barsky and Sims (2011), which is specifically designed to identify the type of shock we focus upon here: a shock that predicts subsequent changes in TFP. These two methods are closely related. Basically, our implementation of the max share method and Barsky and Sims' method looks for a shock which appears to cause future movements in TFP. We can then examine how such a shock, which contains information about future TFP, affects macroeconomic fluctuations. Furthermore, by comparing the results from these two methods with those from the sign restrictions method, we can study the link between optimism-driven fluctuations and future TFP.

3.1 Identifying Shocks that Anticipate Future Growth in TFP

We begin by fixing notations to facilitate descriptions of the max share method and Barsky and Sims' method. Without loss of generality, let TFP be the first element of Y_t and let q denote the unit vector associated with the shock that anticipates future growth in TFP (if such a shock exists). Then, it follows from equation (4) that the share of the forecast error variance (FEV) of TFP attributable to this shock at a finite horizon h, which is denoted by $\Omega_1(h)$, can be expressed as:

$$\Omega_1(h) = q'\mathbf{F}_1(h)\, q, \tag{8}$$

where $\mathbf{F}_1(h)$ is an $n \times n$ positive-definite, symmetric matrix:

$$\mathbf{F}_1(h) = \left(\sum_{k=0}^{h} C_1(k)' \, C_1(k)\right) \Big/ \left(\sum_{k=0}^{h} C_1(k)\, C_1(k)'\right). \tag{9}$$

We can now describe the max share method that is originally proposed by Francis et al. (2005). The identification assumption they use to identify technology shocks is that such shocks should be the dominant forces of driving measured productivity at very long, but finite horizons. So their method identifies technology shocks as the shock that maximizes the share of the FEV of a measure of technology (e.g., labor productivity in their study) at a finite forecast horizon.[18] We can easily extend this method to identify future TFP growth shocks by incorporating a zero restriction that the impulse response of TFP to the future TFP growth shock is zero on impact.

Now if we assume that there exists a shock that does not have an immediate effect on TFP, but becomes an important factor in TFP at a long, but finite horizon, then we can identify such shocks by solving the following maximization problem given the Cholesky decomposition of Σ_u, $\widetilde{A}_0$:

$$q^* = \arg\max_{q} q'\mathbf{F}_1(h)\, q, \;\; s.t. \;\; (1) \;\; q'q = 1; \;\; (2) \;\; q_1 = 0, \tag{10}$$

where q_1 is the first element of the unit vector q. The second constraint ($q_1 = 0$) imposes the zero restriction that the impact response of TFP to the future TFP growth shock is zero.[19]

Next, we briefly introduce the identification method proposed in Barsky and Sims (2011). Their identifi-

[18] The max share identification assumption essentially allows other shocks to influence technology at all finite horizons over which the max share algorithm is employed.

[19] The impact response of TFP is $C_1(0)\, q = \widetilde{A}_0(1,:)\, q$, where $\widetilde{A}_0(1,:)$ is the first row of $\widetilde{A}_0$. Given the Cholesky decomposition of Σ_u (i.e., $\widetilde{A}_0(1,1) \neq 0$ and $\widetilde{A}_0(1,j) = 0$ for $j > 1$), the zero restriction that the impact response of TFP is zero (i.e., $\widetilde{A}_0(1,:)\, q = 0$) collapses to $q_1 = 0$.

cation assumption is that TFP is driven by only two shocks. One is a contemporaneous shock to TFP that has immediate impact on the level of TFP. The other one is a shock that has no contemporaneous effect on TFP, but portends to a change in TFP in the future. They refer to this second shock as a news shock. Here, we want to be more agnostic about the nature of such a shock, since it could represent the effect of advanced information that agents may have about future productivity, i.e., a news shock, or alternatively it could reflect the endogenous response of TFP to some other shocks. An important assumption in their method is that there are precisely two shocks that account for all the FEV of TFP at all horizons. Barsky and Sims' approach therefore differs from the max share method for identifying future TFP growth shocks in a sense that the max share method allows other shocks (e.g., measurement error shocks to TFP) to influence TFP at least at some horizons. As a result, measurement errors in TFP may have larger impact on Barsky and Sims' method than the max share method as we will discuss later.

In a multivariate VAR setting, it is unreasonable to expect that two TFP shocks will explain all of the FEV of TFP at all horizons. So Barsky and Sims propose to identify contemporaneous and future (news) TFP shocks by making such restriction hold as closely as possible over a finite subset of horizons. With contemporaneous shocks to TFP being identified simply as innovations in TFP, identifying future (news) TFP shocks under their method amounts to solving the following maximization problem given the Cholesky decomposition of Σ_u, $\widetilde{A}_0$:[20]

$$q^* = \arg\max_q \sum_{h=0}^{H} \Omega_1(h), \ s.t. \ (1) \ q'q = 1; \ (2) \ q_1 = 0, \tag{11}$$

where $\sum_{h=0}^{H} \Omega_1(h) = q'\mathbf{F}_1(H)q$ is the sum of the shares of the FEV of TFP attributable to future TFP shocks over a finite subset of horizons and $\mathbf{F}_1(H) = \sum\limits_{h=0}^{H} \mathbf{F}_1(h)$. Note that in equation (11), q_1 is the first element of the unit vector q and the second constraint $q_1 = 0$ indicates that the impact response of TFP to future (news) TFP shocks is zero.

From equations (10) and (11), we know that the max share method identifies future TFP shocks such that their contribution to the FEV of TFP is maximized at a finite horizon h, while Barsky and Sims' method identifies future (news) TFP shocks such that their contribution to the FEV of TFP is maximized over all horizons up to a finite truncation horizon H. The relevant Lagrange problems for the maximization problems in equations (10) and (11) imply that the solution takes the form: $q^* = \begin{pmatrix} 0 & q_{(2)}^{*\prime} \end{pmatrix}'$, where $q_{(2)}^*$ is the $(n-1) \times 1$ eigenvector that corresponds to the largest eigenvalue of a $(n-1) \times (n-1)$ sub-matrix of $\mathbf{F}_1(h)$ in the max share method, or a $(n-1) \times (n-1)$ sub-matrix of $\mathbf{F}_1(H)$ in the Barsky and Sims'

[20] It is worthwhile noting that when employing the sign restrictions and max share methods, we can also identify contemporaneous shocks to TFP as innovations in TFP as in Barsky and Sims' method.

method. The sub-matrix is obtained by eliminating the first row and the first column of $\mathbf{F}_1(h)$ or $\mathbf{F}_1(H)$. The choice of the finite horizon h in the max share method and the truncation horizon H in Barsky and Sims' method is to some extent, arbitrary. So before comparing across different methods in the next section, we first consider the effect of h and H on the results of these two methods by focusing on OLS point estimates under different values of h and H.[21]

Figure 8 presents the point estimates of the impulse responses to a future TFP growth shock identified by the max share method with varying h. We consider three different values of the finite horizon h at which the FEV of TFP is maximized: 40, 80, and 120 quarters. The left and right panels show results for the five- and seven-variable systems that we considered in previous sections, respectively. In both systems, TFP does not rise above zero until about ten quarters. Stock price and consumption jump above zero immediately following the identified future TFP growth shock. The real interest rate also increases immediately. Hours, investment, and output all rise significantly above zero and reach their peaks before TFP starts to rise. However, the impact responses of these three variables are sensitive to the value of the finite horizon h. When h is set to 40 quarters, hours, investment, and output in the seven-variable system decline very slightly on impact of a future TFP growth shock. In contrast, when h is set to 80 or 120 quarters, these three variables do not change or slightly increase on impact in response to a future TFP shock. Note that the results of $h = 80$ are very similar to that of $h = 120$. In sum, the impulse responses of variables to the future TFP shock identified by the max share method is robust when the finite horizon h is set to a relatively large value.

Figure 9 displays the point estimates of the impulse responses following the shock that is identified by Barsky and Sims' method with varying H. We also consider three values of the truncation horizon H over which $\sum_{h=0}^{H} \Omega_1(h)$ is maximized: 40, 80, and 120 quarters. The results in Figures 8 and 9 are qualitatively similar. However, a noticeable difference is that Barsky and Sims' method seems more sensitive to the choice of the truncation horizon H than the max share method is to the choice of the finite horizon h. This is particularly true for relatively small h and H: when h and H are set to 40 quarters, hours, investment, and output decline quite substantially on impact when using Barsky and Sims' method as compared to the max share method. Moreover, TFP in the seven-variable system tends to rise immediately after the impact of a future TFP shock identified by setting H equal to 40 quarters. These results echo findings in Barsky and Sims (2011) – which use the truncation horizon of 40 quarters – that a favorable news/future TFP shock leads to declines in hours, investment and output, while TFP rises immediately after the impact of the identified shock. However, these declines become negligible or turn into slight increases and TFP does not

[21] When employing the max share and Barsky and Sims' methods, we estimate the same VAR specification as the one in the sign restrictions method: a constant and four lags are included and all variables enter the system in levels.

rise above zero until about ten quarters when H is set to 80 or 120 quarters. As in the max share method, the results of $H = 80$ are very similar to that of $H = 120$.

4 Comparing across Different Methods

As a first comparison of the different methods, we present in Figure 7 the OLS point estimates of the impulse responses to an optimism shock identified under the three sets of sign restrictions described in Table 1. This figure confirms that the results under these three identification schemes are qualitatively very similar, and therefore, we can concentrate on comparing one set of these responses to the responses associated with future TFP growth shocks.

Figure 10 displays the estimates of impulse responses to the shocks we identified using three different methods: the sign restrictions (Identification III), max share ($h = 80$), and Barsky and Sims ($H = 80$) methods. The left and right panels show results for our five-variable and seven-variable systems, respectively. In the five-variable system, we also consider the method used in Beaudry and Portier (2006) to identify news shocks by imposing a combination of the short- and long-run restrictions in the VECM.[22] Although the algorithms for identifying the shocks in these four methods are very different, the impulse responses obtained from these methods are shockingly similar. In Figure 10, it can be seen that the impulse responses are almost identical for all variables across these methods.

Table 4 reports the correlations between the identified shocks from different methods. We calculate such correlations for both adjusted TFP and non-adjusted TFP. When utilization-adjusted TFP is used, shocks identified from all methods are almost perfectly correlated. The correlation is 0.90 or higher in all cases for both the five- and seven-variable systems. In particular, the correlation between shocks identified from the sign restrictions method and the max share method is 0.98 in the five-variable system and 0.95 in the

[22] The VECM for the five-variable system allows for four cointegrating relationships, an unrestricted constant term, and three lags beyond the error correction term. The short- and long-run restrictions we impose to identify news shocks to TFP are as follows. Assuming that the first (i.e., contemporaneous shocks to TFP) and second (i.e., news shocks to TFP) shocks are the only shocks that have permanent impacts on TFP, we impose the long-run restrictions that the (1,3), (1,4), and (1,5) elements of the long-run (LR) impact matrix are equal to zero. For the short-run restrictions, the assumption that only contemporaneous shocks to TFP have immediate effect on TFP imposes the restrictions that the (1,2), (1,3), (1,4), and (1,5) elements of the short-run (SR) impact matrix are equal to zero. In addition, the assumption that the fourth shock (i.e., monetary shocks) does not affect hours worked immediately imposes the restriction that the (5,4) element of the SR impact matrix is equal to zero, and the interpretation of the fifth shock as measurement error shocks to hours imposes the restrictions that the (2,5) and (3,5) elements of the SR impact matrix are equal to zero. Then, we recuperate the second shock as news shocks to TFP. Note that replacing the above restriction that the (5,4) element of the SR impact matrix equals zero with either the (2,4) or (3,4) element of the SR matrix equals zero do not affect recuperation of the second shock as news shocks to TFP. Our results are also robust when replacing the above restriction that the (2,5) and (3,5) elements of the SR impact matrix equal zero with either the (2,5) and (4,5) elements of the SR impact matrix equal zero or the (3,5) and (4,5) elements of the SR impact matrix equal zero. For the seven-variable system, we do not consider Beaudry and Portier's method because it is not clear how to implement it in such a large system. For the max share and Barsky and Sims' methods, the finite horizon h in the former and the truncation horizon H in the latter are set to 80 quarters.

seven-variable system. When non-adjusted TFP is used, the correlation remains very high except for those associated shocks identified from Barsky and Sims' method. For instance, the correlation between shocks identified from the sign restrictions method and the max share method is 0.94 in the five-variable system and 0.89 in the seven-variable system. However, the correlation between shocks identified from the sign restrictions method and Barsky and Sims' method declines to about 0.60 when non-adjusted TFP is used. When TFP is not adjusted for utilization, the measured TFP contains transitory changes of utilization following the shocks. The sign restrictions method only imposes impact restrictions and the max share method only imposes restrictions on TFP at a long horizon, at which the dynamics of utilization have probably already died out. In contrast, Barsky and Sims' method imposes restrictions on TFP over all horizons up to a truncation horizon. Therefore, when non-adjusted TFP is used, the dynamics of utilization rate may have more undesirable impact on the identification of future TFP growth shocks under Barsky and Sims' method than under the max share method.

The shock identified from the sign restrictions method is aimed at capturing changes in agents' sentiment about the future. The shock that is identified from the max share method is aimed at capturing shocks that affect future TFP movements. The fact that shocks identified from these two different strategies are almost perfectly correlated suggests that the initial changes in sentiment either contain substantial news about future productivity, or somehow cause future productivity growth.

Table 5 presents the forecast error variance (FEV) that is attributable to the identified shocks under different identification methods when utilization-adjusted TFP is used. All methods generate similar results in both five- and seven-variable systems. These shocks explain only a small fraction of the FEV of TFP at horizons of 16 quarters or less, but a significant fraction (about 30%) at a horizon of 40 quarters.[23] The shocks account for more than 60% of the FEV of consumption and close to 50% of the FEV of hours at horizons 8 to 40 quarters under all methods.[24] They also explain more than 40% of the FEVs of investment and output under all methods. Given the similarity of the impulse responses to these shocks and of their importance in explaining business cycle fluctuations, they call for a unified interpretation. Our interpretation is that these shocks reflect bouts of optimism and pessimism that have some grounding in rationality. Either these bouts of optimism and pessimism reflect news about future develpments in TFP, or they cause such developments. At this point we cannot differentiate between these two views as the methods used cannot distinguish between such forces.

Given the importance of our identified optimism shocks in explaining movements in hours worked at

[23]There is one exception. Under Barsky and Sims's method, 15% of the FEV of TFP at horizon 16 quarters is attributable to the identified shocks.

[24]Under Barsky and Sims's method, a relatively small fraction of the FEV of hours is explained by future (news) TFP shocks.

business cycle frequencies, we pursue our analysis by asking the question: if we looked for the shock that best explained the variance of hours worked, would this shock look like a bout of optimism? To explore this issue, we use the max share method to identify a shock that maximizes fluctuations in hours worked at business cycle frequencies (from 8 to 32 quarters). This exercise is closely related to one performed by Uhlig (2003) for GDP. Then we compare the identified shock with our optimism shock identified from the sign restrictions method. Figure 11 presents the estimates of the impulse responses. The blue lines with circles (triangles) are impulse responses to a positive shock identified by maximizing the forecast error variance of hours at a horizon of 8 (32) quarters. The solid lines are impulse responses to a positive optimism shock identified from the sign restrictions method using Identification III in Table 1. Impulse responses to these shocks are again very similar. The shock that maximizes its contribution to the FEV of hours accounts for over 90% of their FEV, and it generates dynamics that can easily be interpreted as reflecting optimism. These results suggest that most of what we observe as business cycle fluctuations may well reflect one common cause: changes in optimism and pessimism. Moreover, given the fact that these changes are associated with long-run movements in TFP, they suggest that they either have a self-fulfilling component or reflect news.

We finish this section by discussing the relationship between our results and those in Barsky and Sims (forthcoming). Barsky and Sims (forthcoming) use measures of consumer confidence from the Michigan survey within the confines of a structural model to explore similar issues to those of the current paper. In particular, Barsky and Sims (forthcoming) show that survey measures of consumer confidence contain substantial information about future developments in the economy, both in terms of economic activity and in terms of subsequent TFP growth. Although at first glance their findings may appear very similar to ours, they are in fact quite different. We will therefore begin by clarifying the substantive differences between the two sets of results in terms of their implication for business cycle theory. We then present empirical results that help explain the source of the differences and offer a reconciliation.

The main difference between our results and those of Barsky and Sims (forthcoming) relates to how innovations reflected in confidence or optimism – which we can use interchangeably in this discussion – affect economic activity and by how many periods is the lag between such innovations and subsequent growth in TFP. The results in Barsky and Sims (forthcoming) suggest that an innovation in consumer confidence, which they interpreted as mainly reflecting news about future TFP growth, precedes eventual TFP growth by only one quarter. Furthermore, their analysis suggests that on impact such a shock leads to an increase in consumption but a fall in investment. This characterization of the effects of "news" shocks is also consistent with that reported in Barsky and Sims (2011).[25] An interesting aspect of this pattern is that it is qualitatively

[25] Barsky and Sims (2011) emphasize that news shocks appear to cause a fall in hours until TFP starts increasing.

consistent with the predictions of an RBC type model where agents receive information about subsequent TFP growth one period in advance. In fact, Barsky and Sims' (forthcoming) analysis goes one step further and argues that the joint behavior of consumer confidence and output is quantitatively consistent with the mechanisms emphasized in the RBC literature.[26] For example, their findings indicate that an increase in confidence of itself does not lead to increased economic activity. According to them, the eventual increase in economic activity following an increase in consumer confidence only arises once TFP starts growing. They therefore conclude that the expansion which follows a news/confidence shock is actually driven by the contemporaneous rise in TFP as in the RBC literature, not by the change in expectations.[27] For these reasons, it appears fair to say that according to Barsky and Sims' work, mood swings are not a very important force driving business cycles and that the effects of confidence are easily explained within the confines of prevalent DSGE models.

In contrast, the results presented in this paper suggest that bouts of optimism and pessimism are key drivers of business cycles, since our identified optimism shocks are associated with a broad based expansion that precedes an eventual rise in productivity by 8 to 12 quarters. If such a characterization is valid, it poses an important challenge to standard DSGE models as such prolonged expectations-driven outcomes are hard to explain in the absence of a substantial rise in inflation or important modifications of the framework. For this reason, it is important to explain the sources of the differences between our work and that of Barsky and Sims, and offer a reconciliation. To this end, in Figure 12 we report four sets of results based on our five-variable system, where we simply replace the stock price measure with the consumer confidence index used by Barsky and Sims (and described in Section 2).[28] The first three panels report impulse responses where we use sign restrictions to identify optimism/confidence shocks. In the first panel, we use an analogue to our sign-restriction based identification scheme, Identification I, where we only impose the restriction that the optimism shock leads to an increase in consumer confidence and has no contemporaneous effect on TFP. In the second panel, we add the sign restriction that the optimism shock also leads to an increase in consumption. And in the third panel, we have the analogue to our Identification III, where we add the positive sign restriction on the impulse response of the real interest rate. In the fourth panel, we use our variant of the Francis et al. method to identify a shock to future TFP growth, where we choose a horizon of 80 quarters to implement the method. As we noted previously, this later method is likely to isolate shocks

[26]Barsky and Sims (forthcoming) actually argue that the response of the economy to news shocks can be explained well using a New Keynesian model in which the monetary authority has a strong anti-inflationary stance. Since they estimate that monetary authorities do not inflate the economy in response to news shocks, the mechanisms at play for explaining the expansion resulting from news are essentially those put forward by the RBC literature.

[27]To be more precise, Barsky and Sims assert that "output movements occur because output tracks movement in true technology not because news shocks induce large business cycle deviations from trend."

[28]Using the seven-variable system gives similar results.

that predict delayed but permanent increases in TFP.

There are two main observations from Figure 12 we want to emphasize. First, if we look at the first panel, we observe a pattern that is generally consistent with the view proposed by Barsky and Sims (forthcoming) regarding how confidence shocks affect the economy; the identified shock leads to immediate rises in confidence and consumption but no increase in hours worked. After one quarter, TFP starts to rise and so do hours worked. Hence, as argued by Barsky and Sims, these observed patterns for consumption and hours can be rather easily explained by standard mechanisms. Although Barsky and Sims (forthcoming) do not use a SVAR approach to make their case, this figure captures the crux of their narrative. However, if we look at the three next panels, we get a substantially different picture. Here, we see that the initial expression of optimism or confidence predates an eventual rise in TFP by at least 8 quarters. Interestingly, we get this result whether we use the sign restrictions or max share methods to identify the underlying shocks. Moreover, during this rather long period where there is no increase in TFP, we observe a large rise in hours worked which peaks at a time where TFP has virtually not yet started to rise. Accordingly, these panels present an expansion which is driven by the optimism itself, not by the mechanisms emphasized in the RBC literature. One can also easily see that the observations from these last three panels closely mimic the main results we reported in the two previous sections.[29] Accordingly, the question becomes whether the observations from the first panel are a better description of how the economy reacts to optimism/confidence shocks or whether they are outliers. Obviously, from the large set of results we present in this paper we believe that the patterns in the first panel are less robust and therefore should be seen as less reliable. More to the point, we believe it reasonable to interpret the difference in the results observed between the first panel and the other panels as indicating that consumer confidence measures are less informative than stock prices as a measure of generalized optimism. When measured consumer confidence is combined with observation on consumption decisions, then it paints a picture of how optimism affects economic activity similar to that obtained from using stock prices alone (here we are comparing the first panel of Figure 1 with the second panel of Figure 12). Such a pattern is precisely what would be expected if survey based measures of consumer confidence often lag actual grassroots decisions by individuals to buy stocks and to buy consumption goods. While we can quite easily reproduce the results of Barsky and Sims (2011 and forthcoming), and their results are coherent and provide a compelling story, we believe that the results of this paper – which echo those previously found by Beaudry and Portier (2006) and Beaudry and Lucke (2010) using alternative identification schemes – offer a more thorough and robust description of how optimism and/or news affects

[29] With the exception of the results in Section 3 where we used the identification method proposed in Barsky and Sims (2011) over the truncation horizon of 40 quarters.

the economy.

5 Conclusion

Many economic commentators view sentiments of optimism and pessimism as important drivers of business cycle fluctuations. In this paper, we began by exploring this issue using sign-restriction based identification schemes to isolate macroeconomic fluctuations that appear most likely driven by such mood swings. Our findings suggest that optimism and pessimism shocks may be the main driving force of business cycles. We identified these shocks using a combination of increases in stock prices, consumer expenditures and survey measures of consumer confidence. We find that such shocks lead to gradual and substantial pick-ups in investment, hours worked and a temporary increase in the real interest rate. During the expansion phase, we do not observe any increase in productivity, nor do we see a pick-up in inflation. Such expansion may be best described as demand-driven but non-inflationary. In this respect, our results differ quite substantially from results presented in Barsky and Sims (forthcoming) which pursue a similar issue using different methodology.[30] Providing a structural model capable of quantitatively replicating the effects of optimism we documented in this paper is in our view an important challenge to model builders.[31]

The second question we ask in the paper is whether our identified optimism and pessimism shocks should be interpreted as mainly reflecting psychological phenomena or should they be seen as potentially grounded in rationality. We explored this second issue along two dimensions. First, we documented that our identified optimism shocks are followed after 2 to 3 years by an increase in measured TFP.[32] While such a pattern is consistent with a "news" interpretation of the initial optimism, it is also potentially consistent with a self-fulfilling belief mechanism. We then examined the issue from a different angle. We used maximum forecast error variance methods, as proposed by Francis et al. (2005) and Barsky and Sims (2011), to identify shocks that preced eventual rises in TFP. We examined whether such shocks are correlated with our identified

[30]By focusing mainly on survey measures of consumer confidence – as opposed to using more broad based indicators of confidence such as stock prices and consumer expenditures – we believe that this Barsky and Sims study likely failed to grasp the full impact of confidence (or mood) on the macro-economy.

[31]As in all cases with structural VARs, some readers may be skeptical of the structural interpretation we give to the shocks isolated from the sign restrictions method. However, even if one is skeptical of our interpretation, we believe our empirical findings pose an interesting challenge to model builders. In particular, at the end of Section 2 we documented that the shock that maximizes its contribution to the forecast error variance of hours worked at business cycle frequencies shares all the same properties as those of our optimism shocks. As the shock resulting from this identification scheme accounts for around 95% of the variance of hours, it offers a nice target to model builders, that is, trying to write down a business cycle model where there is either a reduced-form shock or a structural shock that can account for over 95% of the forecast error variance of hours at business cycle frequencies and the shock has the properties of our optimism shocks. This is a challenge we hope to pursue in the future.

[32]These results echoed the findings in Beaudry and Portier (2006) and Beaudry and Lucke (2010) regarding the effects of news shocks.

optimism shocks. With one exception,[33] we find that the two types of shocks are very highly correlated suggesting that virtually all predictable and permanent increases in TFP are proceeded by a boom period, and that all bouts of optimism are followed by an eventual rise in TFP. The relationship is so strong – a correlation of over 0.9 – that it opens up the question of whether the relationship can reasonably be given a pure "news" interpretation or alternatively if they may more reasonably reflect a causal force going from optimism to subsequent growth in TFP. As this question is beyond the scope of the paper, we see it as a second challenge to the literature.

[33] The one exception corresponds to the case where we used the method proposed by Barsky and Sims (2011) and chose a short truncation horizon. In this case, we found that optimism shocks are only weakly correlated with shocks that predict future TFP growth.

References

[1] Akerlof, George and Robert J. Shiller, 2009. "Animal Spirits: How Human Psychology Drives the Economy and Why it matters for Global Capitalism," *Princeton University Press*, 264pp.

[2] Barsky, Robert and Eric Sims, 2011. "News Shocks and Business Cycles," *Journal of Monetary Economics* 58(3): 273-289.

[3] Barsky, Robert and Eric Sims, forthcoming. "Information, Animal Spirits, and the Meaning of Innovations in Consumer Confidence," *American Economic Review*.

[4] Basu, Susanto, John G. Fernald, and Miles S. Kimball, 2006. "Are Technology Improvements Contractionary?" *American Economic Review* 96: 1418-1448.

[5] Beaudry, Paul, Martial Dupaigne, and Franck Portier, 2011. "The International Propagation of News Shocks," *Review of Economic Dynamics* 14(1): 72-91.

[6] Beaudry, Paul and Bernd Lucke, 2010. "Letting Different Views about Business Cycles Compete," *NBER Macroeconomics Annual 2009*, Volume 24, 413-455.

[7] Beaudry, Paul and Franck Portier, 2004. "An Exploration into Pigou's Theory of Cycles," *Journal of Monetary Economics* 51(6): 1183-1216.

[8] Beaudry, Paul and Franck Portier, 2006. "Stock Prices, News, and Economic Fluctuations," *American Economic Review* 96(4): 1293-1307.

[9] Bernanke, Ben and Ilian Mihov, 1998. "Measuring Monetary Policy," *Quarterly Journal of Economics* 113(3): 869-902.

[10] Benabib, Jess and Roger Farmer, 1994. "Indeterminacy and Increasing Returns," *Journal of Economic Theory* 63(1): 19-41.

[11] Blanchard, Olivier J. and Danny Quah, 1989. "The Dynamic Effects of Aggregate Demand and Supply Disturbances," *American Economic Review* 79(4): 655-673.

[12] Cochrane, John H., 1994a. "Shocks," *Carnegie-Rochester Conference Series on Public Policy* 41: 295-364.

[13] Cochrane, John H., 1994b. "Permanent and Transitory Components of GNP and Stock Prices," *Quarterly Journal of Economics* 109(1): 241-265.

[14] Dedola, Luca and Stefano Neri, 2007. "What Does a Technology Shock Do? A VAR Analysis with Model-based Sign Restrictions," *Journal of Monetary Economics* 54: 512-549.

[15] Enders, Zeno, Gernot Muller, and Almuth Scholl, 2011. "How do Fiscal and Technology Shocks Affect Real Exchange Rates? New Evidence for the United States," *Journal of International Economics* 83: 53-69.

[16] Engel, Charles and Ken D. West, 2005. "Exchange Rates and Fundamentals," *Journal of Political Economy* 113: 485-517.

[17] Farmer, Roger and Jang Ting Guo, 1994. "Real Business Cycles and the Animal Spirits Hypothesis," *Journal of Economic Theory* 63(1): 42-72.

[18] Francis, Neville, Michael T. Owyang, Jennifer E. Roush, and Riccardo DiCecio, 2005. "A Flexible Finite-Horizon Alternative to Long-run Restrictions with an Application to Technology Shocks", Working Paper 2005-024F, Federal Reserve Bank of St. Louis.

[19] Gali, Jordi, 1999. "Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations?" *American Economic Review* 89(1): 249-271.

[20] Jaimovich, Nir and Sergio Rebelo, 2009. "Can News About the Future Drive the Business Cycle?" *American Economic Review* 99(4): 1097-1118.

[21] Mountford, Andrew and Harald Uhlig, 2009. "What Are the Effects of Fiscal Policy Shocks?" *Journal of Applied Econometrics* 24: 960-992.

[22] Nam, Deokwoo and Jian Wang, 2010a. "Understanding the Effect of Productivity Changes on International Relative Prices: The Role of News Shocks," Globalization and Monetary Policy Institute Working Paper No. 61.

[23] Nam, Deokwoo and Jian Wang, 2010b. "The Effects of News About Future Productivity on International Relative Prices: An Empirical Investigation," Globalization and Monetary Policy Institute Working Paper No. 64.

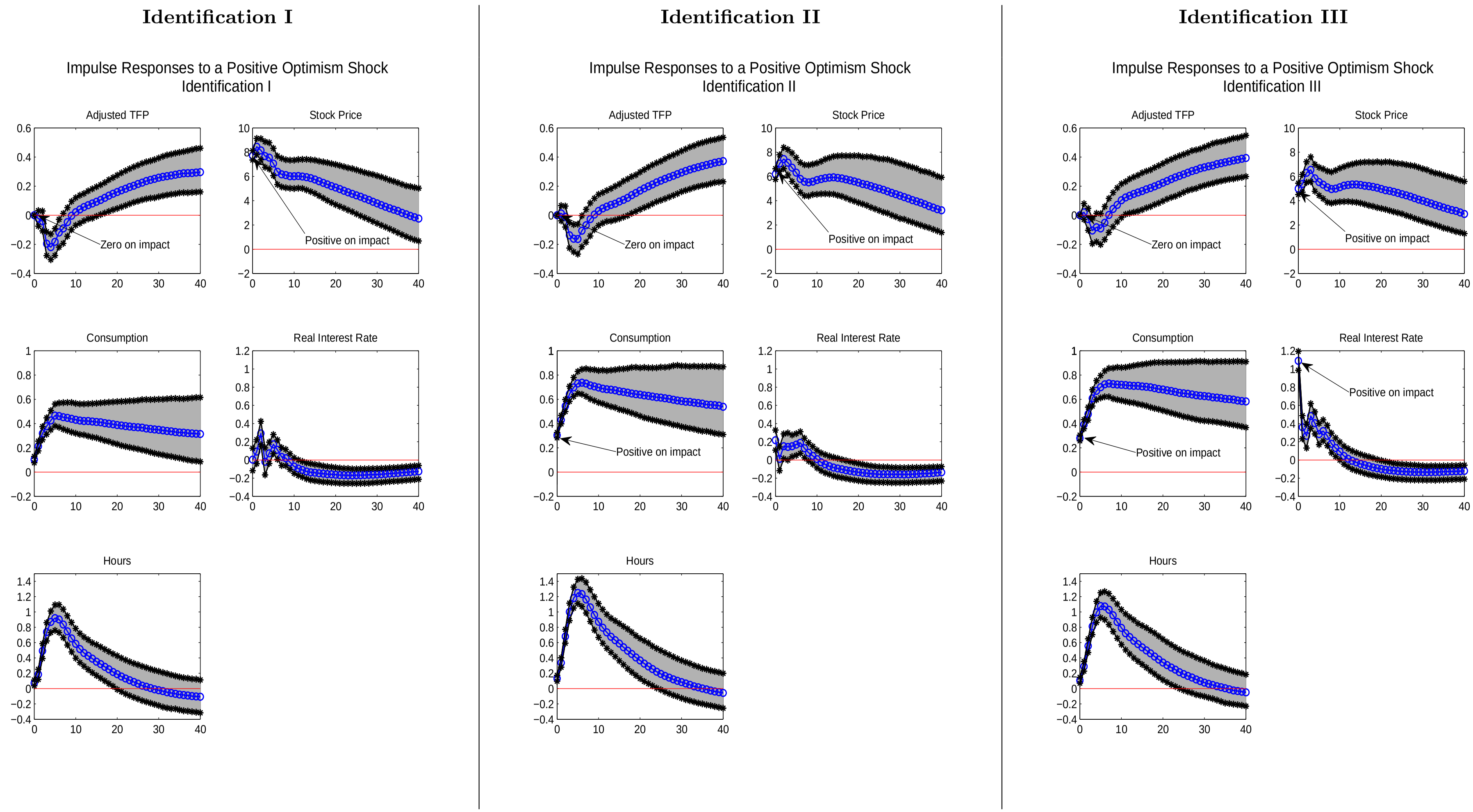
[24] Peersman, Gert and Roland Straub, 2009. "Techonology Shock and Robust Sign Restrictions in a Euro Area SVAR," *International Economic Review* 50(3): 727-750.

[25] Schmitt-Grohe, Stephanie and Martin Uribe, 2009. "What's News In Business Cycles?" Working Paper, Columbia University.

[26] Uhlig, Harald, 2003. What Drives GNP? mimeo, 2003.

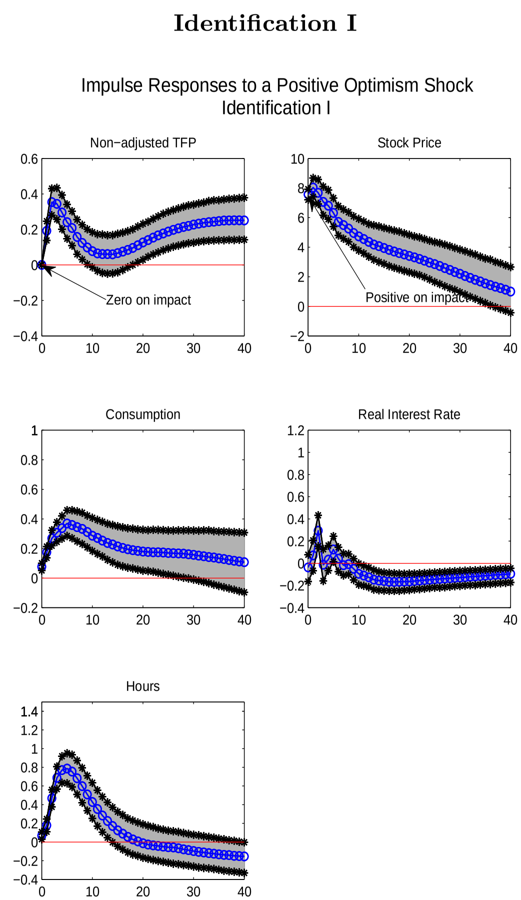
[27] Uhlig, Harald, 2005. "What Are the Effects of Monetary Policy on Output? Results from an Agnostic Identification Procedure," *Journal of Monetary Economics* 52: 381-419.

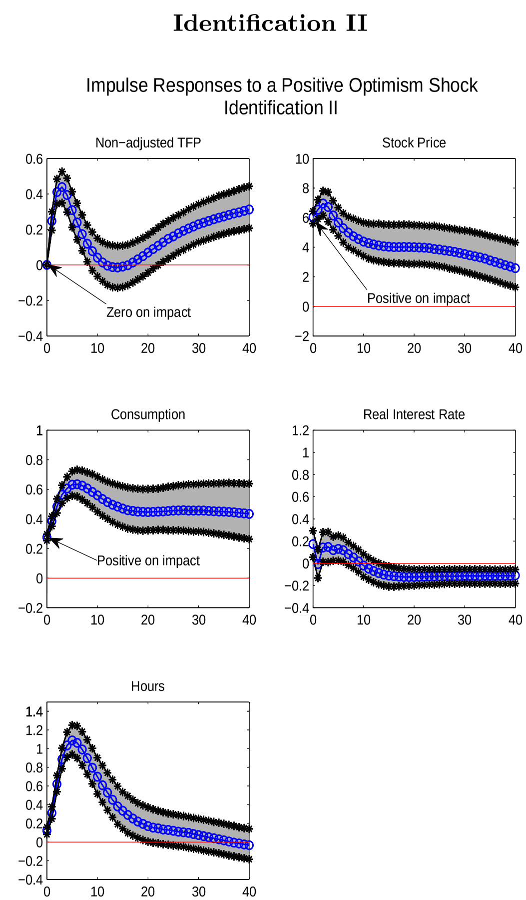
Figure 1: Impulse Responses to a Positive Optimism Shock in the Five-variable System with Adjusted TFP

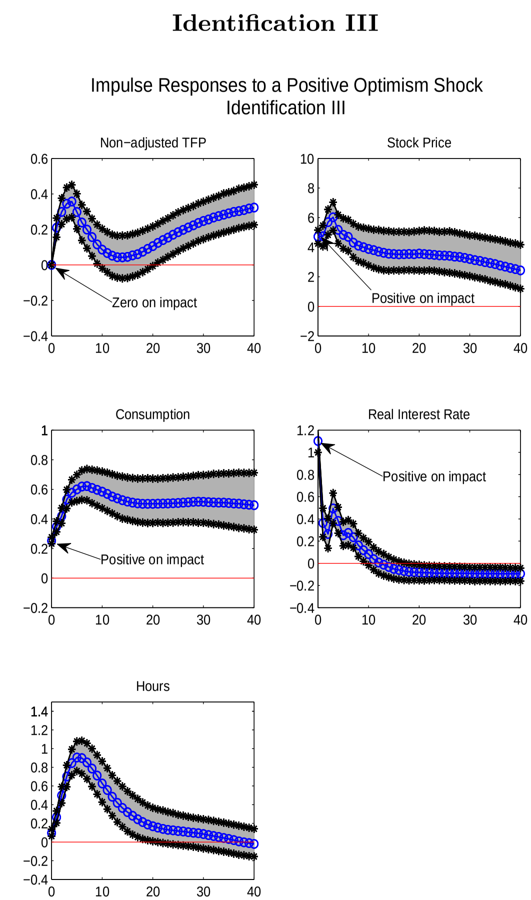


This figure has three panels each of which displays impulse responses to a unit optimism shock identified by imposing each of sign restrictions, that is, Identification I (left panel), Identification II (middle panel), and Identification III (right panel) that are described in Table 1, in the five-variable system with (BFK's Adjusted TFP, Stock Price, Consumption, Real Interest Rate, Hours). The line with circles represents the median response and the grayed-area with starred lines represents the 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 2: Impulse Responses to a Positive Optimism Shock in the Five-variable System with Non-adjusted TFP

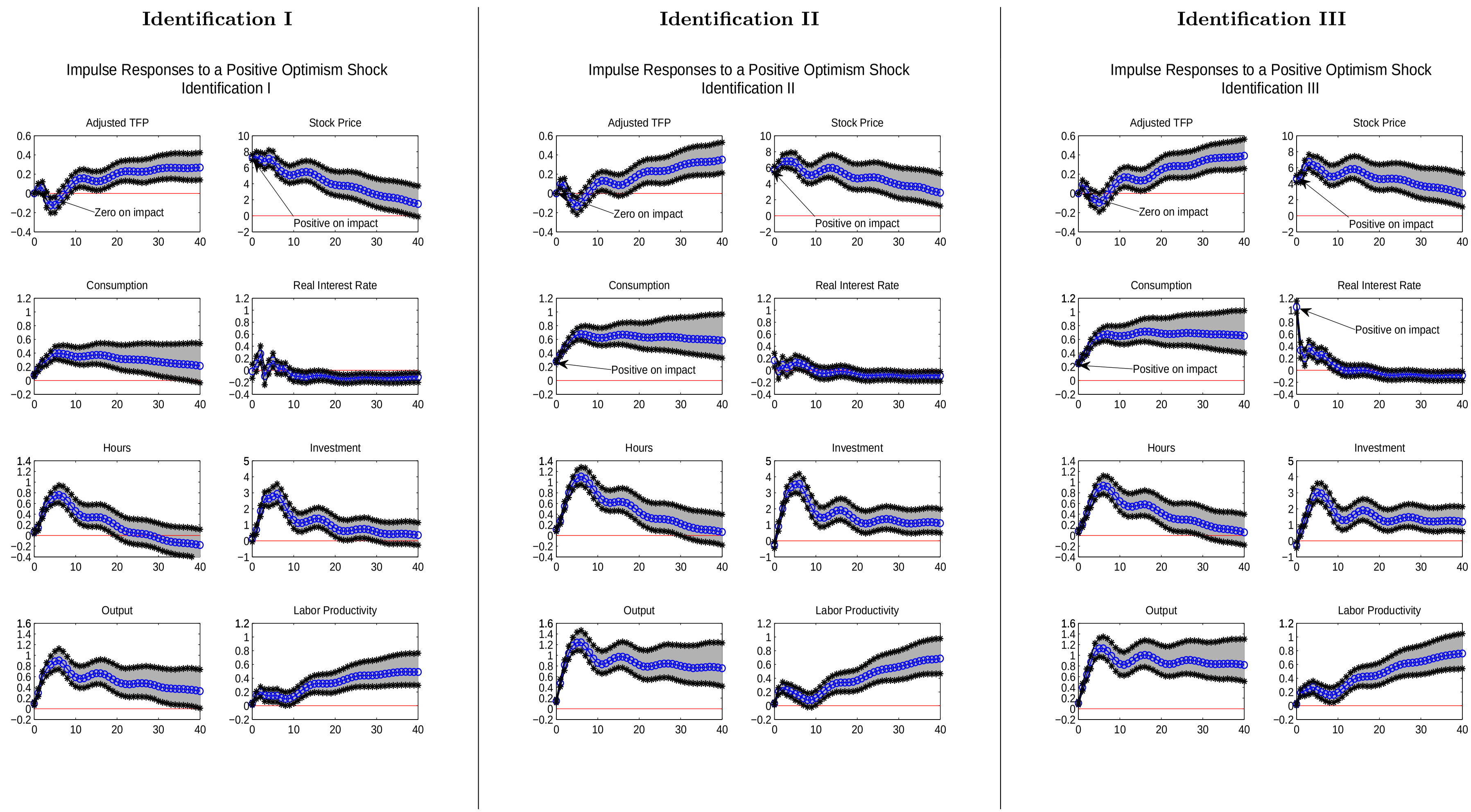






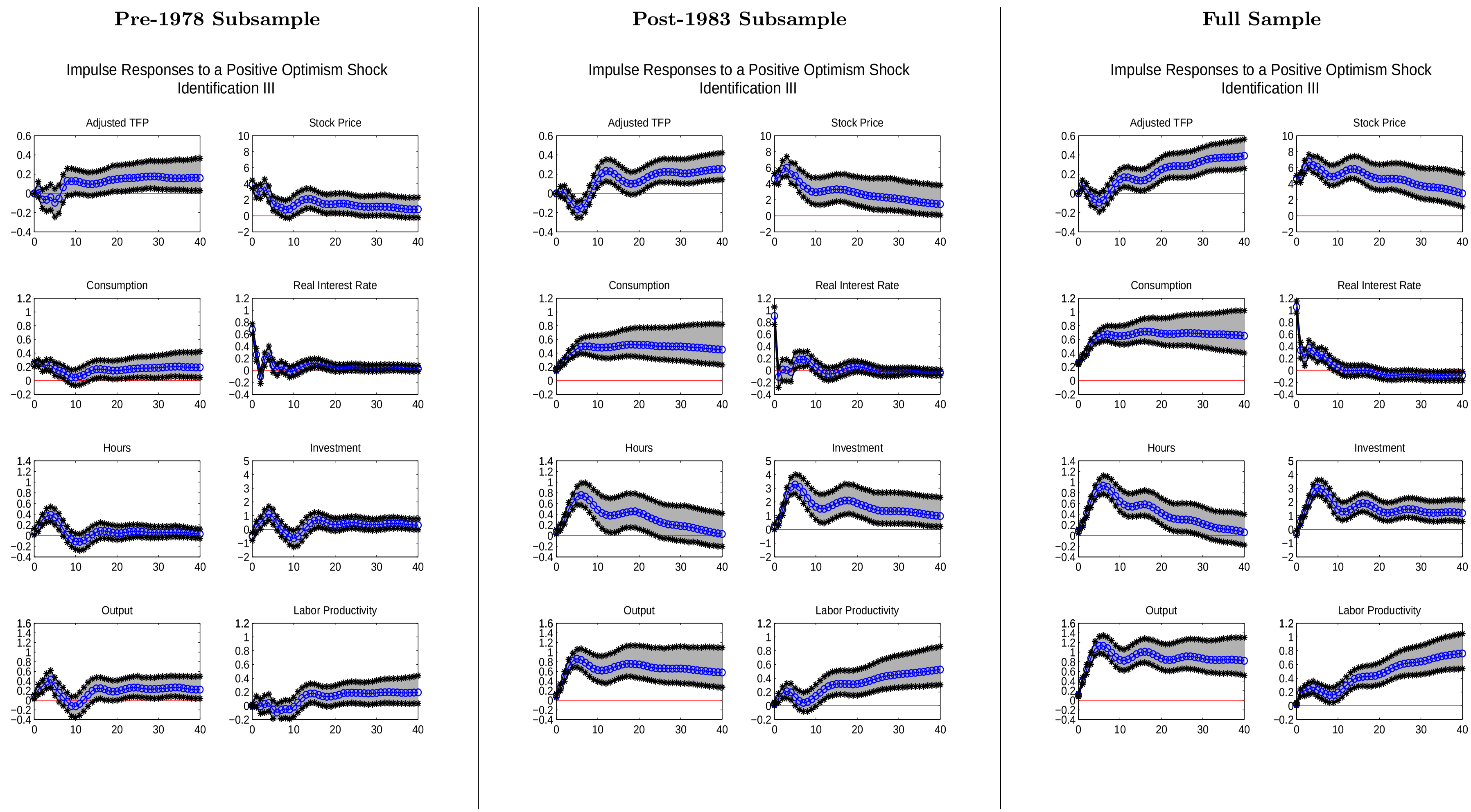
This figure has three panels each of which displays impulse responses to a unit optimism shock identified by imposing each of sign restrictions, that is, Identification I (left panel), Identification II (middle panel), and Identification III (right panel) that are described in Table 1, in the five-variable system with (BFK's Non-adjusted TFP, Stock Price, Consumption, Real Interest Rate, Hours). The line with circles represents the median response and the grayed-area with starred lines represents the 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 Responses to a Positive Optimism Shock in the Seven-variable System



This figure has three panels each of which displays impulse responses to a unit optimism shock identified by imposing each of sign restrictions, that is, Identification I (left panel), Identification II (middle panel), and Identification III (right panel) that are described in Table 1, in the seven-variable system with (BFK's Adjusted TFP, Stock Price, Consumption, Real Interest Rate, Hours, Investment, Output). Response of Labor Productivity is calculated from those of Output and Hours. The line with circles represents the median response and the grayed-area with starred lines represents the 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.

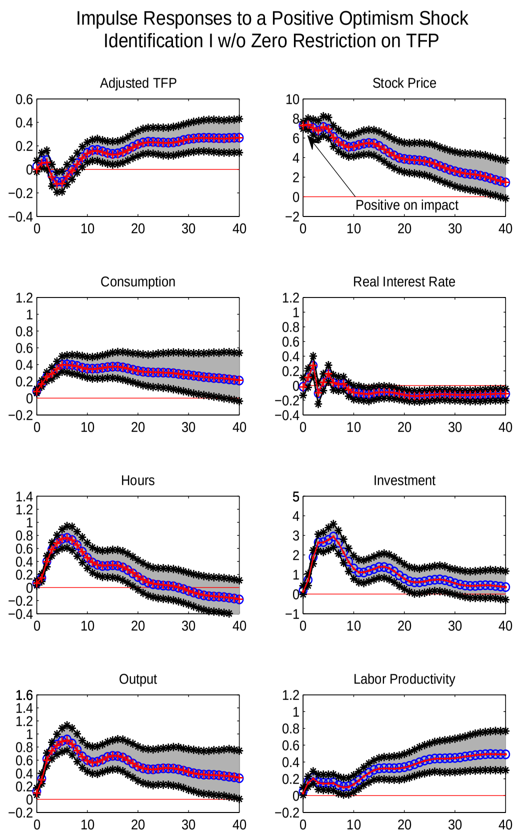
Figure 4: Impulse Responses to a Positive Optimism Shock Identified in Subsamples in the Seven-variable System



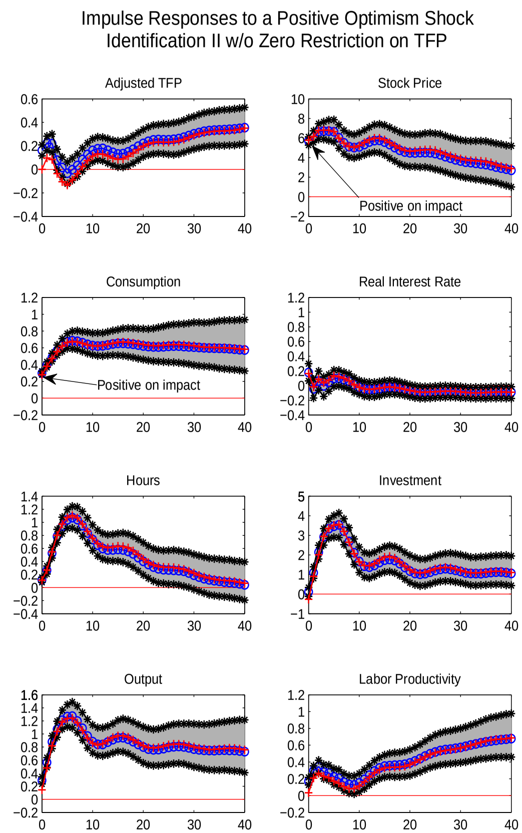
This figure has three panels each of which displays impulse responses to a unit optimism shock identified by imposing sign restrictions of Identification III (right panel) in either the pre-1978 subsample period from 1955:Q1 to 1978:Q4 (left panel), the post-1983 subsample period from 1983:Q1 to 2010:Q4 (middle panel), or the full sample period from 1955:Q1 to 2010:Q4 (right panel) in the seven-variable system with (BFK's Adjusted TFP, Stock Price, Consumption, Real Interest Rate, Hours, Investment, Output). Response of Labor Productivity is calculated from those of Output and Hours. The line with circles represents the median response and the grayed-area with starred lines represents the 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 5: Impulse Responses to a Positive Optimism Shock Identified without Zero Restriction on TFP in the Seven-variable System

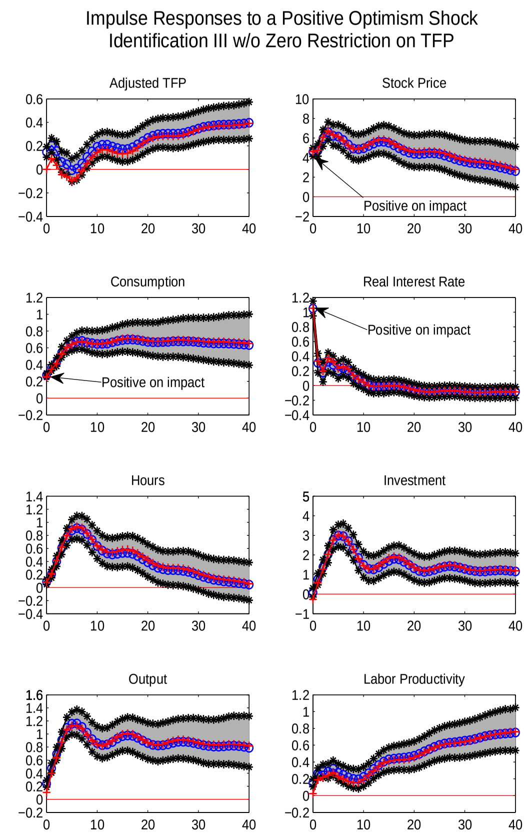
Identification I w/o Zero Restriction on TFP



Identification II w/o Zero Restriction on TFP

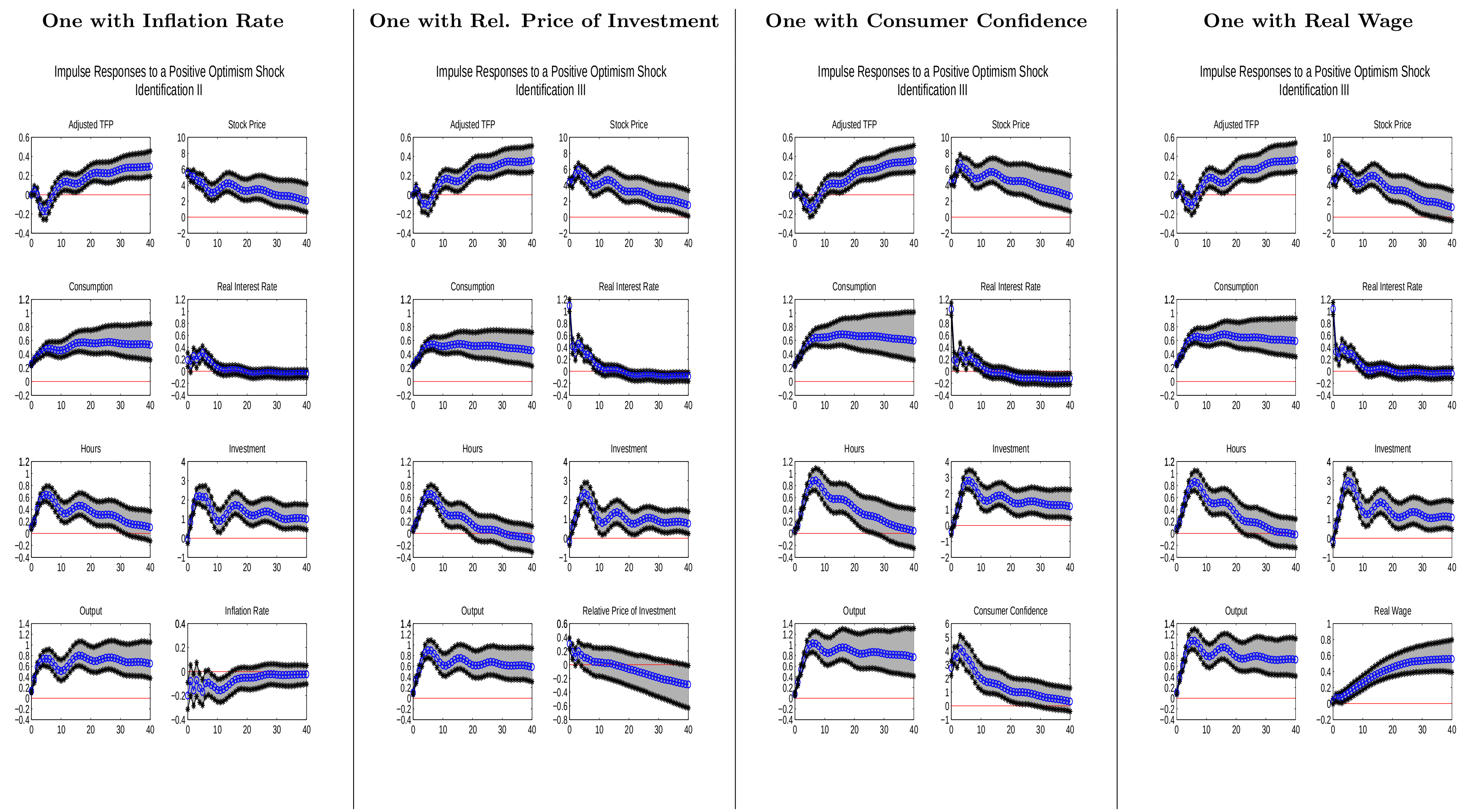


Identification III w/o Zero Restriction on TFP



This figure has three panels each of which displays impulse responses to a unit optimism shock identified by imposing each of three different sets of sign restrictions in which the zero restriction that the impulse response of TFP is zero on impact is not imposed in the seven-variable system with (BFK's Adjusted TFP, Stock Price, Consumption, Real Interest Rate, Hours, Investment, Output). The line with circles represents the median response and the grayed-area with starred lines represents the 16th and 84th quantiles. For the reference, the median impulse responses under our original sign restrictions (that is, those with the zero restriction on TFP) are plotted by the lines with (red-colored) crosses. The unit of the vertical axis is percentage deviation from the situation without shock and the unit of the horizontal axis is quarter.

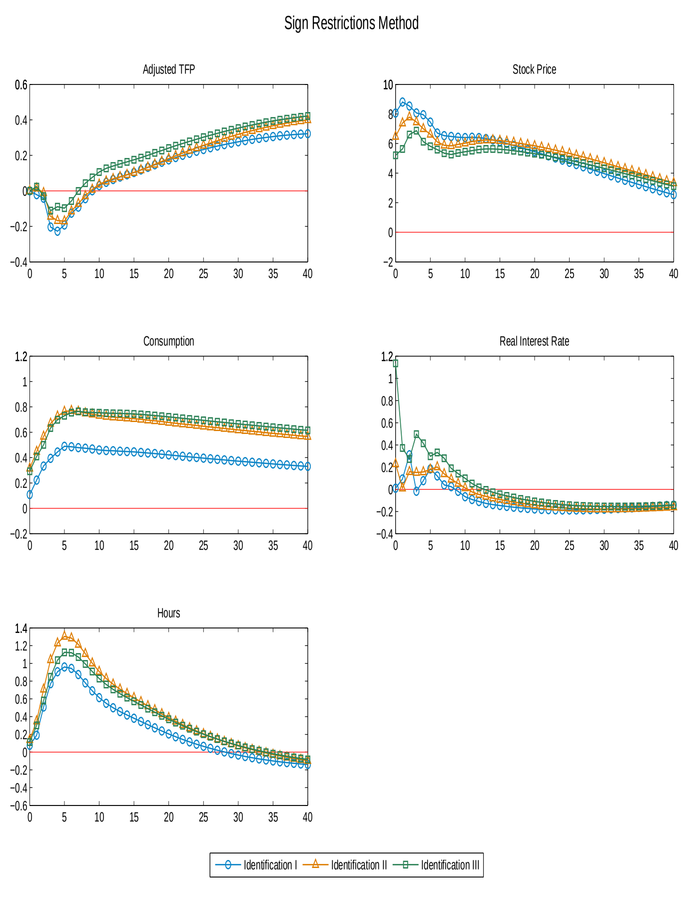
Figure 6: Impulse Responses to a Positive Optimism Shock in the Eight-variable Systems



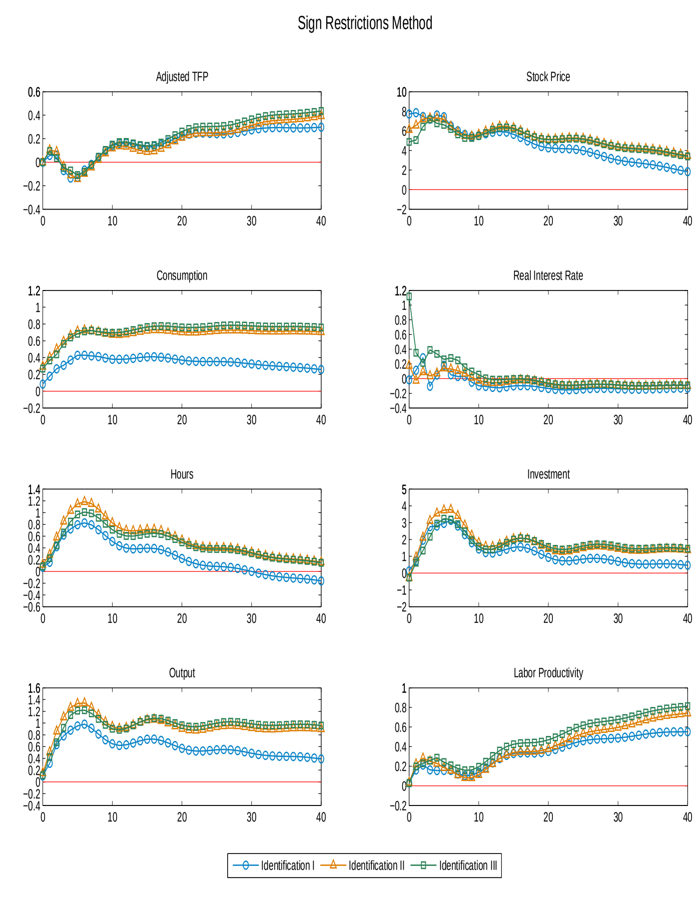
This figure has four panels each of which displays impulse responses to a unit optimism shock in an eight-variable system where either CPI Inflation Rate (the first panel), Relative Price of Investment (the second panel), Consumer Confidence (the third panel), or Real Wage (the fourth panel) is added to the seven-variable system. In the system with CPI Inflation Rate, optimism shocks are identified by imposing Identification II, and in the system with Relative Price of Investment (Consumer Confidence or Real Wage), optimism shocks are identified by imposing Identification III. The sample period for the system with Consumer Confidence is 1960:Q1 to 2010:Q4. The line with circles represents the median response and the grayed-area with starred lines represents the 16th and 84th quantiles. The unit of the vertical axis is percentage deviation from the situation without shock (for Consumer Confidence, it is points) and the unit of the horizontal axis is quarter.

Figure 7: Impulse Responses to a Positive Optimism Shock Identified by the Sign Restrictions Method

Five-variable System



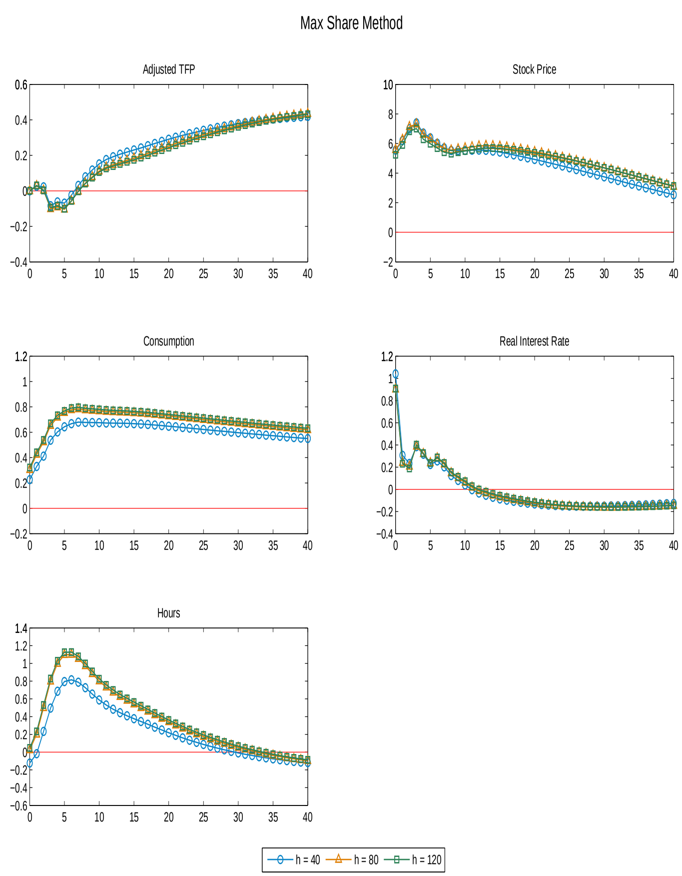
Seven-variable System



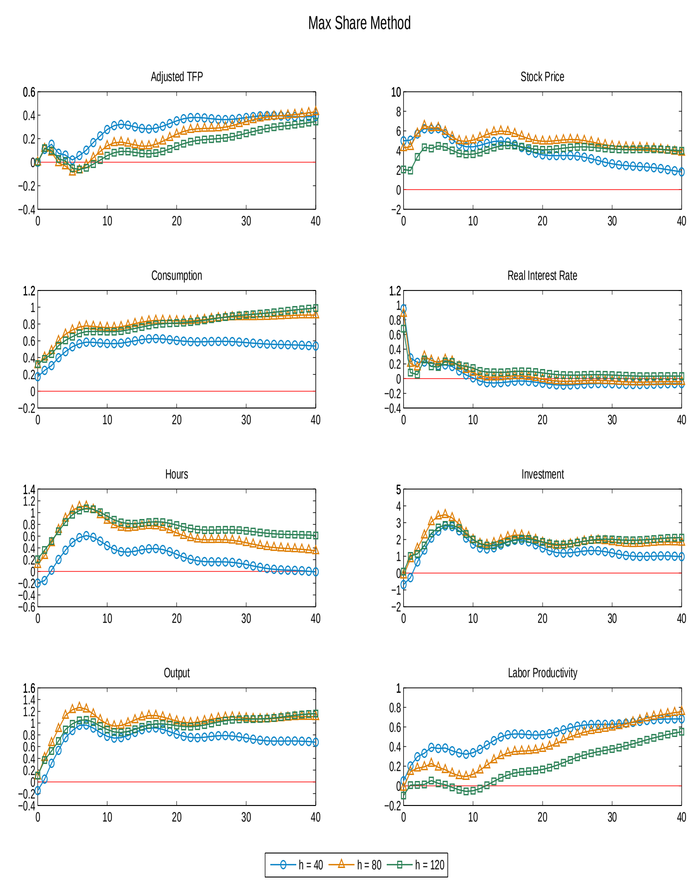
This figure has two panels each of which displays OLS point estimates of impulse responses to a unit optimism shock identified by imposing each of sign restrictions, that is, Identification I, II, and III that are described in Table 1. The left panel is the five-variable system with (BFK's Adjusted TFP, Stock Price, Consumption, Real Interest Rate, Hours). The right panel is the seven-variable system with (BFK's Adjusted TFP, Stock Price, Consumption, Real Interest Rate, Hours, Investment, Output) where the impulse response of Labor productivity is calculated from those of Output and Hours. The unit of the vertical axis is percentage deviation from the situation without shock and the unit of the horizontal axis is quarter.

Figure 8: Impulse Responses to a Positive Future TFP Growth Shock Identified by the Max Share Method

Five-variable System



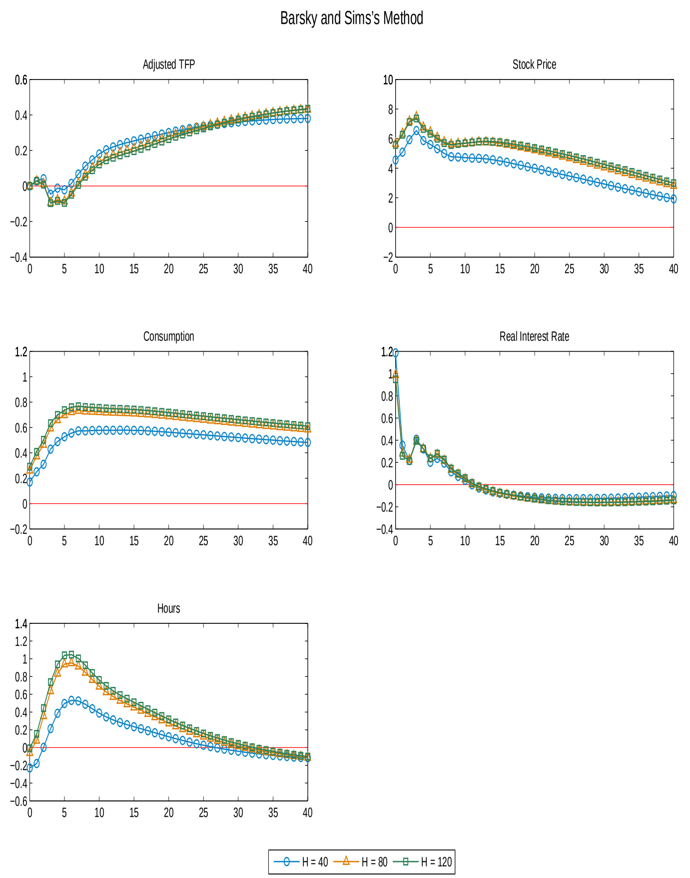
Seven-variable System



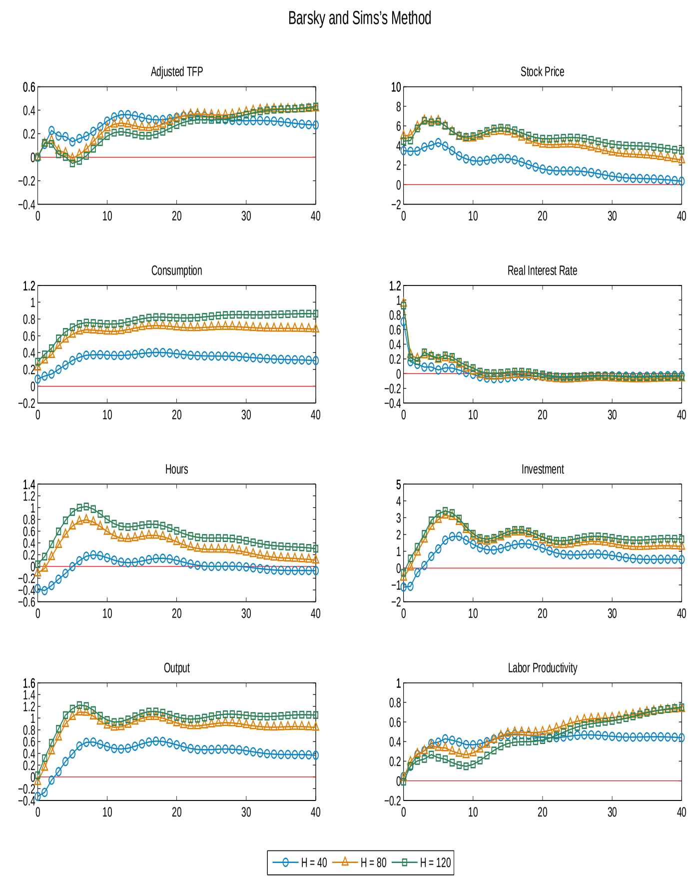
This figure has two panels each of which displays OLS point estimates of impulse responses to a unit future TFP growth shock identified by Max Share Method with the finite horizon (h) equal to one of 40, 80, and 120 quarters. The left panel is the five-variable system with (BFK's Adjusted TFP, Stock Price, Consumption, Real Interest Rate, Hours). The right panel is the seven-variable system with (BFK's Adjusted TFP, Stock Price, Consumption, Real Interest Rate, Hours, Investment, Output) where the impulse response of Labor productivity is calculated from those of Output and Hours. The unit of the vertical axis is percentage deviation from the situation without shock and the unit of the horizontal axis is quarter.

Figure 9: Impulse Responses to a Positive Future TFP Growth Shock Identified by Barsky and Sims' Method

Five-variable System



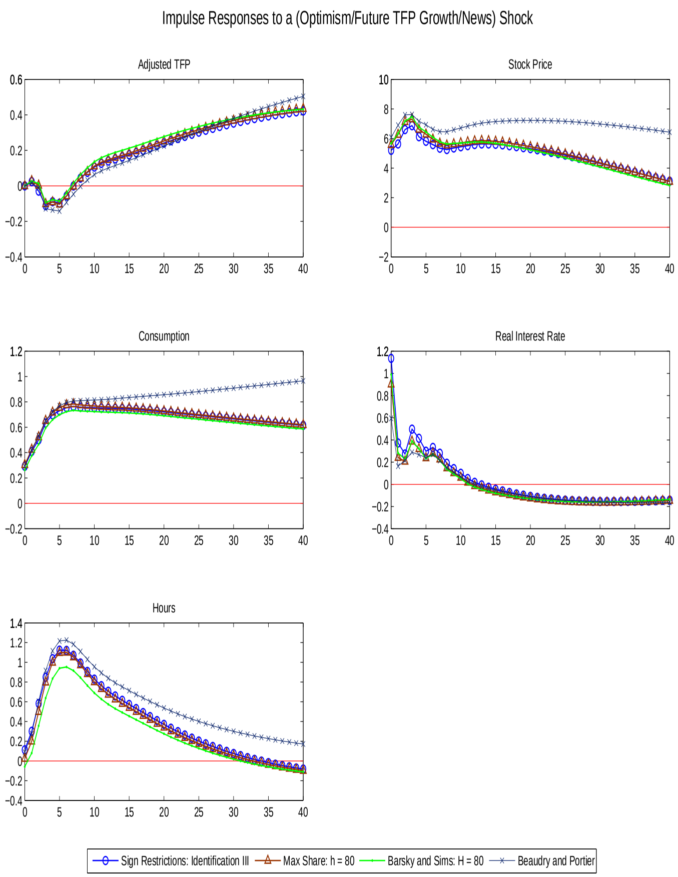
Seven-variable System



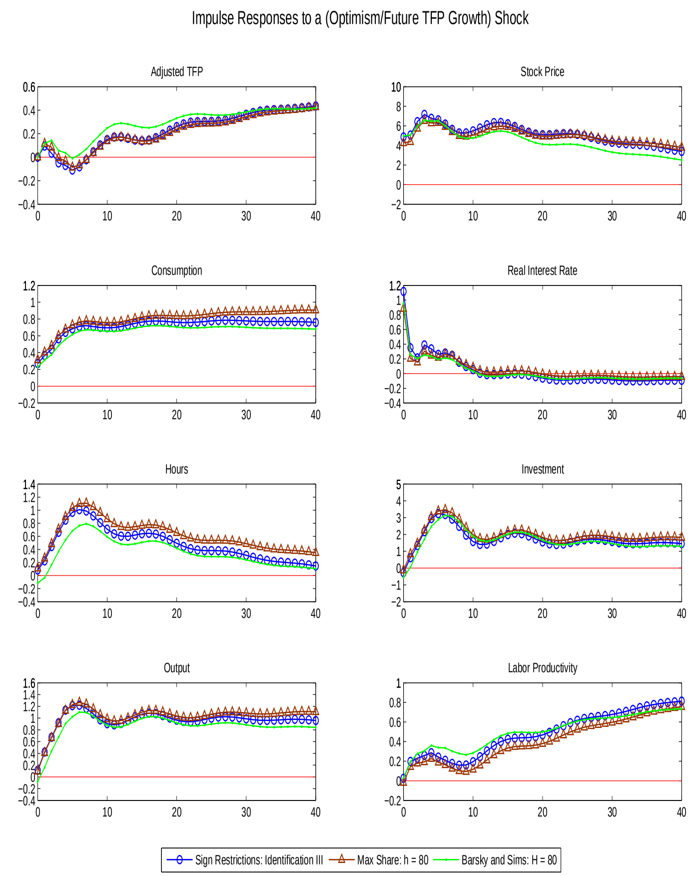
This figure has two panels each of which displays OLS point estimates of impulse responses to a unit future TFP growth shock identified by Barsky and Sims' Method with the truncation horizon (H) equal to one of 40, 80, and 120 quarters. The left panel is the five-variable system with (BFK's Adjusted TFP, Stock Price, Consumption, Real Interest Rate, Hours). The right panel is the seven-variable system with (BFK's Adjusted TFP, Stock Price, Consumption, Real Interest Rate, Hours, Investment, Output) where the impulse response of Labor productivity is calculated from those of Output and Hours. The unit of the vertical axis is percentage deviation from the situation without shock and the unit of the horizontal axis is quarter.

Figure 10: Impulse Responses to a Positive (Optimism/Future TFP Growth/News) Shock Identified by Different Methods

Five-variable System



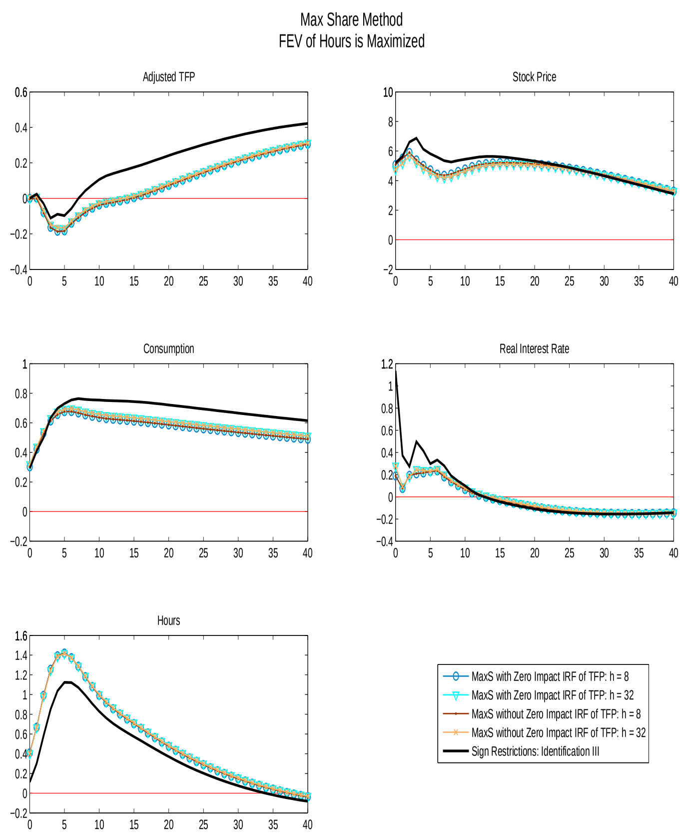
Seven-variable System



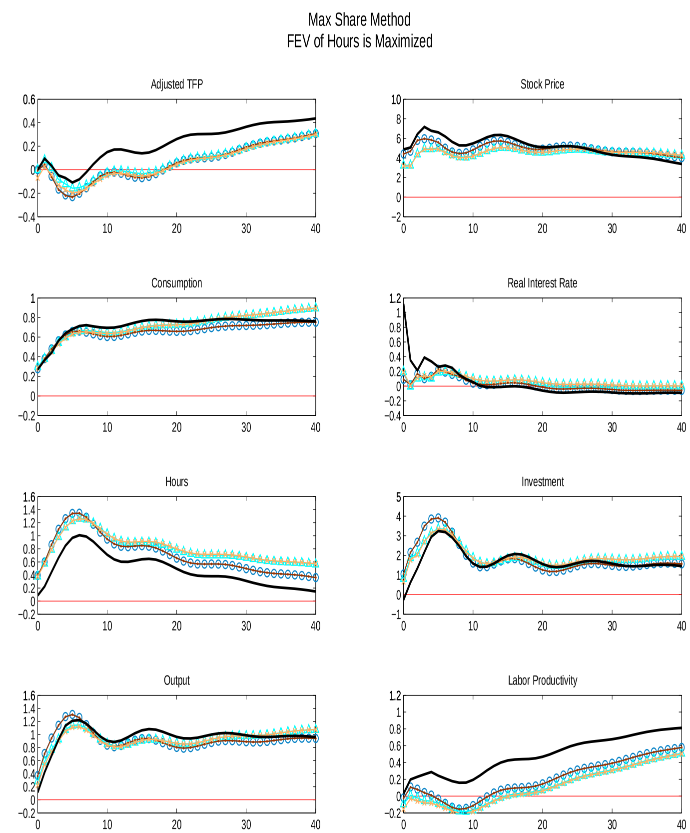
This figure has two panels each of which displays OLS point estimates of impulse responses to a unit (optimism/future TFP growth/news) shock identified by Sign Restrictions Method with Identification III, Max Share Method with the finite horizon (h) of 80 quarters, Barsky and Sims' Method with the truncation horizon (H) of 80 quarters, and Beaudry and Portier's Method that is available only for the five-variable system. The left panel is the five-variable system with (BFK's Adjusted TFP, Stock Price, Consumption, Real Interest Rate, Hours). The right panel is the seven-variable system with (BFK's Adjusted TFP, Stock Price, Consumption, Real Interest Rate, Hours, Investment, Output) where the impulse response of Labor productivity is calculated from those of Output and Hours. The unit of the vertical axis is percentage deviation from the situation without shock and the unit of the horizontal axis is quarter.

Figure 11: Impulse Responses to a Positive Shock Identified by Applying the Max Share Method on Hours

Five-variable System

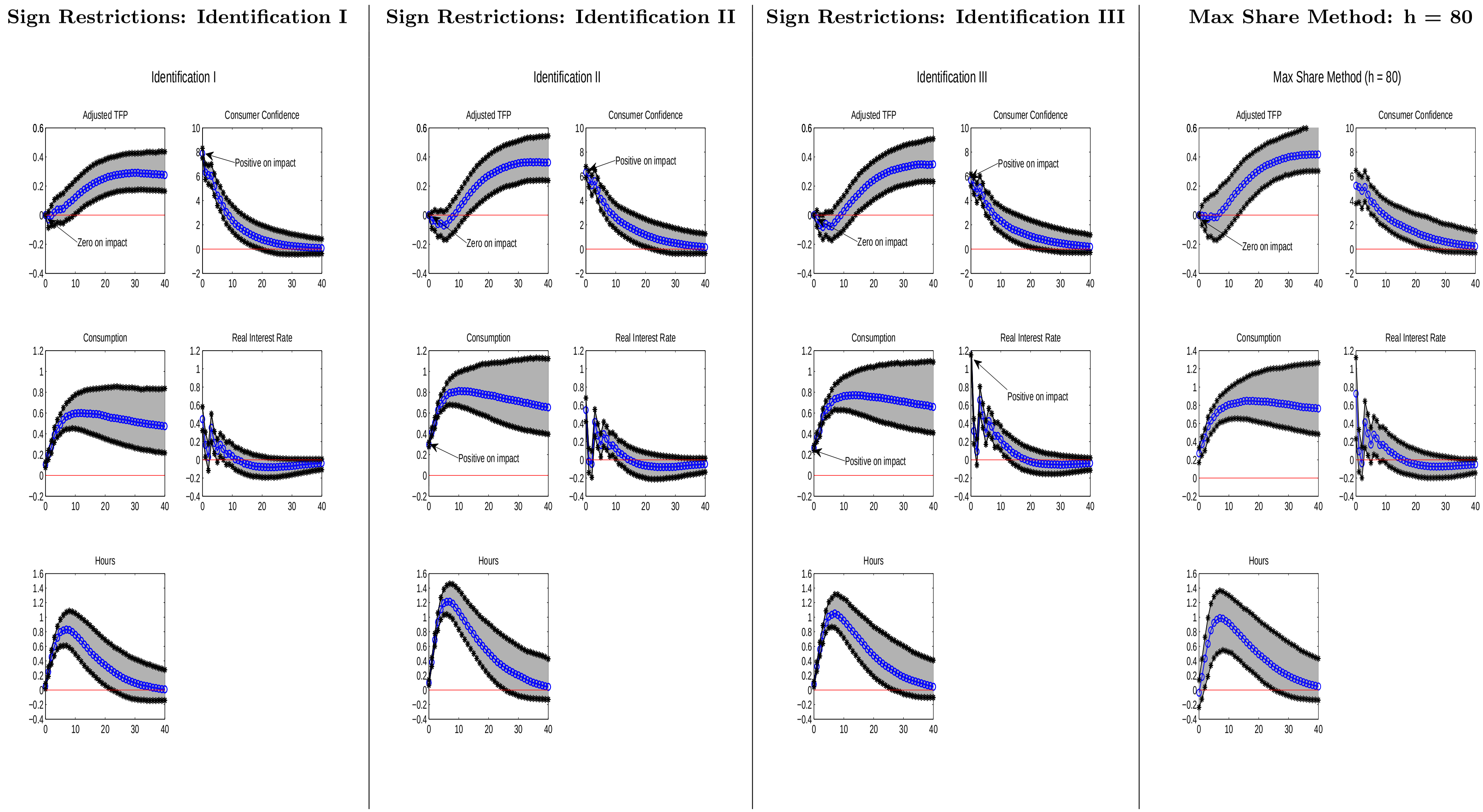


Seven-variable System



This figure has two panels each of which displays OLS point estimates of impulse responses to a shock identified by applying the Max Share Method to Hours Worked in the five-variable (the left panel) and seven-variable (the right panel) systems, respectively: that is, we identify the shock that maximizes its contribution of the forecast error variance (FEV) of Hours at the finite horizon (h) equal to one of 8 and 32, imposing the zero restriction on the impact impulse response of TFP or not imposing such zero restriction. For the reference, the OLS point estimates of impulse responses under sign restrictions, Identification III, are plotted by the (black) bold lines. The unit of the vertical axis is percentage deviation from the situation without shock and the unit of the horizontal axis is quarter.

Figure 12: Impulse Responses in the Five-variable System with Consumer Confidence in Place of Stock Price



This figure has four panels each of which displays impulse responses to a unit identified shock in the five-variable system with Consumer Confidence in place of Stock Price. The first three panels show impulse responses estimated by imposing our three sets of sign restrictions, Identifications I, II, and III, respectively, where the positive sign restriction on the impact impulse response of Consumer Confidence is imposed. The last panel shows impulse responses estimated by using the Max Share method where the forecast error variance of TFP at the finite horizon (h) of 80 quarters is maximized, with the zero restriction on the impact impulse response of TFP. The sample period is 1960:Q1 to 2010:Q4. For all four panels, the line with circles represents the median response and the grayed-area with starred lines represents the 16th and 84th quantiles. The unit of the vertical axis is percentage deviation from the situation without shock (for Consumer Confidence, it is points) and the unit of the horizontal axis is quarter.

Table 1: Sign Restrictions

	TFP	Stock Price	Consumption	Real Interest Rate	Hours	Investment	Output
Identification I	0	+					
Identification II	0	+	+				
Identification III	0	+	+	+			

This table shows three sets of sign restrictions imposed: Identifications I, II, and III. The impulse responses of variables are restricted to be zero (0) on impact, non-negative (+) on impact, or unrestricted (blank) in either the five-variable system with (TFP, Stock Price, Consumption, Real Interest Rate, Hours), the seven-variable system with (TFP, Stock Price, Consumption, Real Interest Rate, Hours, Investment, Output), or the eight-variable systems where an additional variable of interest is added to the seven-variable system.

Table 2: Share of Forecast Error Variance Attributable to Optimism Shocks Identified by Imposing Sign restrictions in the Five-variable System

Panel A: Five-variable System with Adjusted TFP																		
	Identification I						**Identification II**						**Identification III**					
	h = 0	h = 4	h = 8	h = 16	h = 24	h = 40	h = 0	h = 4	h = 8	h = 16	h = 24	h = 40	h = 0	h = 4	h = 8	h = 16	h = 24	h = 40
Adjusted TFP	0.00	0.03	0.04	0.05	0.08	0.18	0.00	0.02	0.03	0.04	0.08	0.22	0.00	0.01	0.02	0.05	0.11	0.28
	[0.00, 0.00]	[0.01, 0.07]	[0.02, 0.09]	[0.03, 0.09]	[0.04, 0.14]	[0.08, 0.29]	[0.00, 0.00]	[0.01, 0.04]	[0.01, 0.07]	[0.02, 0.09]	[0.03, 0.15]	[0.10, 0.37]	[0.00, 0.00]	[0.00, 0.03]	[0.01, 0.05]	[0.02, 0.10]	[0.04, 0.21]	[0.14, 0.42]
Stock Price	1.00	0.93	0.90	0.85	0.80	0.73	0.64	0.71	0.71	0.73	0.74	0.72	0.41	0.51	0.53	0.56	0.58	0.58
	[0.98, 1.00]	[0.89, 0.96]	[0.85, 0.95]	[0.76, 0.92]	[0.68, 0.89]	[0.55, 0.85]	[0.60, 0.68]	[0.64, 0.77]	[0.61, 0.79]	[0.61, 0.82]	[0.60, 0.83]	[0.57, 0.82]	[0.36, 0.46]	[0.43, 0.58]	[0.43, 0.62]	[0.44, 0.68]	[0.43, 0.70]	[0.41, 0.71]
Consumption	0.07	0.27	0.30	0.30	0.28	0.26	0.59	0.81	0.82	0.79	0.76	0.70	0.50	0.71	0.77	0.80	0.80	0.76
	[0.04, 0.10]	[0.19, 0.35]	[0.21, 0.40]	[0.20, 0.41]	[0.17, 0.41]	[0.14, 0.42]	[0.54, 0.63]	[0.76, 0.86]	[0.76, 0.88]	[0.69, 0.86]	[0.63, 0.85]	[0.55, 0.83]	[0.45, 0.55]	[0.64, 0.77]	[0.67, 0.84]	[0.69, 0.88]	[0.66, 0.88]	[0.60, 0.88]
Real Interest Rate	0.00	0.03	0.04	0.06	0.09	0.14	0.01	0.03	0.05	0.06	0.08	0.13	0.37	0.34	0.36	0.34	0.34	0.36
	[0.00, 0.01]	[0.01, 0.05]	[0.02, 0.07]	[0.03, 0.10]	[0.05, 0.15]	[0.08, 0.22]	[0.00, 0.03]	[0.01, 0.06]	[0.02, 0.09]	[0.03, 0.10]	[0.04, 0.15]	[0.08, 0.22]	[0.32, 0.42]	[0.28, 0.40]	[0.29, 0.43]	[0.27, 0.41]	[0.28, 0.41]	[0.29, 0.43]
Hours	0.02	0.30	0.37	0.34	0.32	0.31	0.05	0.56	0.70	0.69	0.66	0.63	0.03	0.38	0.52	0.54	0.52	0.49
	[0.00, 0.04]	[0.22, 0.37]	[0.28, 0.46]	[0.23, 0.45]	[0.21, 0.44]	[0.21, 0.43]	[0.03, 0.09]	[0.48, 0.63]	[0.61, 0.77]	[0.58, 0.77]	[0.54, 0.76]	[0.49, 0.74]	[0.01, 0.06]	[0.31, 0.47]	[0.41, 0.62]	[0.40, 0.66]	[0.37, 0.65]	[0.34, 0.63]
Panel B: Five-variable System with Non-adjusted TFP																		
	Identification I						**Identification II**						**Identification III**					
	h = 0	h = 4	h = 8	h = 16	h = 24	h = 40	h = 0	h = 4	h = 8	h = 16	h = 24	h = 40	h = 0	h = 4	h = 8	h = 16	h = 24	h = 40
Non-adjusted TFP	0.00	0.13	0.12	0.10	0.11	0.18	0.00	0.20	0.19	0.15	0.14	0.22	0.00	0.13	0.14	0.12	0.12	0.22
	[0.00, 0.00]	[0.08, 0.18]	[0.07, 0.20]	[0.06, 0.17]	[0.06, 0.18]	[0.10, 0.28]	[0.00, 0.00]	[0.14, 0.26]	[0.12, 0.26]	[0.10, 0.21]	[0.09, 0.20]	[0.14, 0.32]	[0.00, 0.00]	[0.08, 0.19]	[0.08, 0.22]	[0.07, 0.19]	[0.07, 0.20]	[0.13, 0.33]
Stock Price	0.98	0.92	0.89	0.82	0.75	0.59	0.62	0.70	0.70	0.69	0.68	0.62	0.38	0.46	0.49	0.49	0.50	0.48
	[0.96, 1.00]	[0.87, 0.95]	[0.83, 0.93]	[0.73, 0.89]	[0.63, 0.85]	[0.43, 0.75]	[0.58, 0.66]	[0.63, 0.76]	[0.61, 0.77]	[0.57, 0.78]	[0.56, 0.77]	[0.49, 0.74]	[0.33, 0.43]	[0.38, 0.54]	[0.39, 0.58]	[0.37, 0.61]	[0.38, 0.63]	[0.34, 0.61]
Consumption	0.04	0.19	0.22	0.20	0.17	0.13	0.48	0.68	0.72	0.69	0.64	0.57	0.41	0.58	0.67	0.71	0.70	0.66
	[0.02, 0.06]	[0.13, 0.27]	[0.14, 0.32]	[0.11, 0.30]	[0.08, 0.27]	[0.06, 0.24]	[0.44, 0.54]	[0.61, 0.75]	[0.63, 0.80]	[0.58, 0.78]	[0.52, 0.75]	[0.40, 0.73]	[0.36, 0.46]	[0.50, 0.67]	[0.56, 0.76]	[0.58, 0.81]	[0.55, 0.81]	[0.47, 0.80]
Real Interest Rate	0.00	0.03	0.03	0.06	0.09	0.12	0.01	0.03	0.03	0.05	0.07	0.10	0.37	0.35	0.35	0.33	0.33	0.34
	[0.00, 0.01]	[0.01, 0.05]	[0.02, 0.06]	[0.03, 0.10]	[0.05, 0.14]	[0.07, 0.20]	[0.00, 0.03]	[0.01, 0.05]	[0.01, 0.07]	[0.03, 0.09]	[0.04, 0.12]	[0.06, 0.16]	[0.32, 0.42]	[0.29, 0.41]	[0.29, 0.42]	[0.27, 0.41]	[0.26, 0.40]	[0.26, 0.41]
Hours	0.01	0.25	0.30	0.27	0.25	0.24	0.04	0.44	0.57	0.56	0.51	0.46	0.03	0.29	0.40	0.42	0.39	0.35
	[0.00, 0.03]	[0.18, 0.32]	[0.20, 0.39]	[0.17, 0.37]	[0.16, 0.35]	[0.16, 0.34]	[0.02, 0.07]	[0.37, 0.52]	[0.48, 0.66]	[0.46, 0.66]	[0.40, 0.63]	[0.33, 0.60]	[0.01, 0.05]	[0.22, 0.37]	[0.29, 0.50]	[0.29, 0.54]	[0.26, 0.53]	[0.22, 0.49]

This table has two panels each of which reports the share of forecast error variance attributable to optimism shocks identified by imposing each of sign restrictions, that is, Identification I (left panel), Identification II (middle panel), and Identification III (right panel) that are described in Table 1, in the five-variable system with (TFP, Stock Price, Consumption, Real Interest Rate, Hours) for various forecast horizons. Panel A is that BFK's Adjusted TFP is used and Panel B is that BFK's Non-adjusted TFP is used. The numbers represent the median share, and the numbers in brackets are the 16th and 84th quantiles. The letter h refers to the forecast horizon.

Table 3: Share of Forecast Error Variance Attributable to Optimism Shocks Identified by Imposing Sign Restrictions in the Seven-variable System

Seven-variable System with Adjusted TFP	Identification I						Identification II						Identification III					
	h = 0	h = 4	h = 8	h = 16	h = 24	h = 40	h = 0	h = 4	h = 8	h = 16	h = 24	h = 40	h = 0	h = 4	h = 8	h = 16	h = 24	h = 40
Adjusted TFP	0.00	0.02	0.02	0.05	0.10	0.17	0.00	0.02	0.03	0.05	0.09	0.22	0.00	0.01	0.02	0.06	0.12	0.29
	[0.00, 0.00]	[0.01, 0.03]	[0.01, 0.05]	[0.03, 0.10]	[0.04, 0.18]	[0.08, 0.30]	[0.00, 0.00]	[0.01, 0.03]	[0.02, 0.05]	[0.03, 0.09]	[0.04, 0.18]	[0.09, 0.37]	[0.00, 0.00]	[0.01, 0.03]	[0.01, 0.05]	[0.03, 0.12]	[0.05, 0.24]	[0.14, 0.46]
Stock Price	1.00	0.87	0.82	0.73	0.65	0.53	0.63	0.72	0.71	0.72	0.69	0.63	0.40	0.57	0.59	0.63	0.63	0.58
	[0.99, 1.00]	[0.81, 0.91]	[0.75, 0.88]	[0.63, 0.82]	[0.52, 0.77]	[0.37, 0.70]	[0.58, 0.67]	[0.66, 0.78]	[0.63, 0.79]	[0.61, 0.80]	[0.57, 0.78]	[0.49, 0.74]	[0.35, 0.45]	[0.50, 0.64]	[0.51, 0.68]	[0.53, 0.73]	[0.51, 0.73]	[0.43, 0.70]
Consumption	0.04	0.19	0.23	0.22	0.20	0.15	0.54	0.72	0.73	0.69	0.64	0.55	0.44	0.63	0.69	0.72	0.70	0.64
	[0.02, 0.07]	[0.12, 0.26]	[0.15, 0.32]	[0.13, 0.33]	[0.10, 0.32]	[0.06, 0.29]	[0.49, 0.58]	[0.65, 0.78]	[0.66, 0.81]	[0.59, 0.78]	[0.52, 0.75]	[0.39, 0.69]	[0.40, 0.49]	[0.55, 0.70]	[0.60, 0.77]	[0.60, 0.81]	[0.56, 0.81]	[0.45, 0.77]
Real Interest Rate	0.00	0.03	0.04	0.05	0.07	0.10	0.01	0.02	0.03	0.04	0.05	0.06	0.36	0.30	0.30	0.28	0.27	0.27
	[0.00, 0.01]	[0.02, 0.05]	[0.02, 0.06]	[0.03, 0.09]	[0.04, 0.12]	[0.05, 0.17]	[0.00, 0.03]	[0.01, 0.04]	[0.01, 0.06]	[0.02, 0.07]	[0.02, 0.09]	[0.03, 0.13]	[0.31, 0.41]	[0.25, 0.36]	[0.25, 0.37]	[0.23, 0.35]	[0.22, 0.34]	[0.21, 0.34]
Hours	0.01	0.23	0.29	0.25	0.20	0.18	0.04	0.46	0.60	0.56	0.49	0.39	0.02	0.29	0.42	0.41	0.38	0.30
	[0.00, 0.03]	[0.17, 0.31]	[0.21, 0.38]	[0.15, 0.34]	[0.12, 0.31]	[0.10, 0.28]	[0.02, 0.07]	[0.39, 0.54]	[0.52, 0.68]	[0.46, 0.65]	[0.39, 0.61]	[0.28, 0.54]	[0.01, 0.04]	[0.21, 0.37]	[0.32, 0.52]	[0.29, 0.54]	[0.25, 0.52]	[0.18, 0.46]
Investment	0.00	0.27	0.34	0.33	0.30	0.26	0.01	0.38	0.50	0.49	0.48	0.45	0.01	0.21	0.33	0.36	0.38	0.39
	[0.00, 0.01]	[0.20, 0.34]	[0.26, 0.42]	[0.24, 0.42]	[0.21, 0.40]	[0.17, 0.37]	[0.00, 0.02]	[0.30, 0.45]	[0.41, 0.58]	[0.40, 0.58]	[0.38, 0.58]	[0.34, 0.56]	[0.00, 0.02]	[0.15, 0.28]	[0.24, 0.43]	[0.25, 0.47]	[0.26, 0.50]	[0.26, 0.52]
Output	0.01	0.28	0.34	0.34	0.31	0.24	0.03	0.55	0.67	0.68	0.65	0.59	0.02	0.40	0.54	0.61	0.63	0.62
	[0.01, 0.02]	[0.20, 0.35]	[0.25, 0.43]	[0.24, 0.44]	[0.20, 0.43]	[0.14, 0.39]	[0.02, 0.05]	[0.48, 0.62]	[0.59, 0.74]	[0.59, 0.75]	[0.55, 0.74]	[0.45, 0.71]	[0.01, 0.03]	[0.33, 0.48]	[0.44, 0.63]	[0.49, 0.70]	[0.50, 0.73]	[0.46, 0.73]
Labor Productivity	0.00	0.05	0.05	0.10	0.17	0.24	0.00	0.10	0.09	0.13	0.21	0.39	0.00	0.10	0.11	0.19	0.30	0.51
	[0.00, 0.01]	[0.02, 0.10]	[0.02, 0.11]	[0.04, 0.19]	[0.08, 0.28]	[0.12, 0.39]	[0.00, 0.01]	[0.05, 0.16]	[0.04, 0.15]	[0.06, 0.22]	[0.10, 0.34]	[0.22, 0.56]	[0.00, 0.00]	[0.05, 0.16]	[0.05, 0.18]	[0.09, 0.30]	[0.17, 0.46]	[0.32, 0.66]

This table reports the share of forecast error variance attributable to optimism shocks identified by imposing each of sign restrictions, that is, Identification I (left panel), Identification II (middle panel), and Identification III (right panel) that are described in Table 1, in the seven-variable system with (BFK's Adjusted TFP, Stock Price, Consumption, Real Interest Rate, Hours, Investment, Output). The forecast error variance share of Labor productivity is calculated from those of Output and Hours. The numbers represent the median share, and the numbers in brackets are the 16th and 84th quantiles. The letter h refers to the forecast horizon.

Table 4: Correlation between (Optimism/Future TFP Growth/News) Shocks Identified by Different Methods

Panel A: Adjusted TFP									
Five-variable System					**Seven-variable System**				
	Sign Restrictions: Identification III	Max Share: h = 80	Barsky and Sims: H = 80	Beaudry and Portier		Sign Restrictions: Identification III	Max Share: h = 80	Barsky and Sims: H = 80	Beaudry and Portier
Sign Restrictions: Identification III	1.000				Sign Restrictions: Identification III	1.000			
Max Share: h = 80	0.976	1.000			Max Share: h = 80	0.949	1.000		
Barsky and Sims: H = 80	0.953	0.984	1.000		Barsky and Sims: H = 80	0.904	0.898	1.000	
Beaudry and Portier	0.943	0.972	0.938	1.000	Beaudry and Portier	N/A	N/A	N/A	N/A
Panel B: Non-adjusted TFP									
Five-variable System					**Seven-variable System**				
	Sign Restrictions: Identification III	Max Share: h = 120	Barsky and Sims: H = 120	Beaudry and Portier		Sign Restrictions: Identification III	Max Share: h = 120	Barsky and Sims: H = 120	Beaudry and Portier
Sign Restrictions: Identification III	1.000				Sign Restrictions: Identification III	1.000			
Max Share: h = 80	0.940	1.000			Max Share: h = 80	0.887	1.000		
Barsky and Sims: H = 80	0.628	0.550	1.000		Barsky and Sims: H = 80	0.589	0.817	1.000	
Beaudry and Portier	0.707	0.858	0.104	1.000	Beaudry and Portier	N/A	N/A	N/A	N/A

This table has two panels each of which reports correlations between OLS point estimates of (optimism/future TFP growth/news) shocks identified by Sign Restrictions Method with Identification III, Max Share Method with the finite horizon (h) of 80 quarters, Barsky and Sims's Method with the truncation horizon (H) of 80 quarters, and Beaudry and Portier's Method that is available only for the five-variable system. Panel A and Panel B are that BFK's Adjusted and Non-adjusted TFP as measure of TFP are used, respectively.

Table 5: Share of Forecast Error Variance Attributable to (Optimism/Future TFP Growth/News) Shocks Identified by Different Methods

Panel A: Five-variable System with Adjusted TFP																								
	Sign Restrictions: Identification III						**Max Share: h = 80**						**Barsky and Sims: H = 80**						**Beaudry and Portier**					
	h = 0	h = 4	h = 8	h = 16	h = 24	h = 40	h = 0	h = 4	h = 8	h = 16	h = 24	h = 40	h = 0	h = 4	h = 8	h = 16	h = 24	h = 40	h = 0	h = 4	h = 8	h = 16	h = 24	h = 40
Adjusted TFP	0.00	0.01	0.01	0.04	0.11	0.32	0.00	0.01	0.01	0.04	0.12	0.34	0.00	0.01	0.01	0.05	0.14	0.37	0.00	0.01	0.02	0.03	0.10	0.37
Stock Price	0.42	0.52	0.55	0.61	0.65	0.68	0.48	0.61	0.64	0.68	0.71	0.73	0.49	0.63	0.66	0.69	0.70	0.70	0.62	0.74	0.76	0.80	0.83	0.87
Consumption	0.51	0.72	0.80	0.85	0.88	0.89	0.55	0.77	0.85	0.89	0.91	0.92	0.41	0.63	0.72	0.78	0.80	0.81	0.56	0.82	0.88	0.93	0.94	0.97
Real Interest Rate	0.37	0.35	0.37	0.36	0.36	0.38	0.23	0.21	0.23	0.22	0.23	0.27	0.28	0.25	0.26	0.25	0.26	0.29	0.11	0.12	0.14	0.14	0.15	0.21
Hours	0.03	0.39	0.54	0.58	0.58	0.56	0.00	0.34	0.50	0.54	0.53	0.52	0.01	0.22	0.36	0.39	0.38	0.37	0.02	0.48	0.66	0.72	0.74	0.75
Panel B: Seven-variable System with Adjusted TFP																								
	Sign Restrictions: Identification III						**Max Share: h = 80**						**Barsky and Sims: H = 80**						**Beaudry and Portier**					
	h = 0	h = 4	h = 8	h = 16	h = 24	h = 40	h = 0	h = 4	h = 8	h = 16	h = 24	h = 40	h = 0	h = 4	h = 8	h = 16	h = 24	h = 40	h = 0	h = 4	h = 8	h = 16	h = 24	h = 40
Adjusted TFP	0.00	0.01	0.01	0.05	0.13	0.36	0.00	0.01	0.01	0.04	0.12	0.33	0.00	0.02	0.02	0.13	0.26	0.46	N/A					
Stock Price	0.40	0.59	0.64	0.71	0.73	0.73	0.30	0.48	0.54	0.61	0.65	0.69	0.41	0.54	0.58	0.59	0.58	0.54						
Consumption	0.45	0.65	0.73	0.78	0.79	0.73	0.60	0.75	0.84	0.91	0.93	0.91	0.31	0.48	0.59	0.66	0.67	0.61						
Real Interest Rate	0.36	0.31	0.32	0.30	0.29	0.29	0.23	0.19	0.20	0.19	0.19	0.17	0.26	0.21	0.21	0.20	0.20	0.19						
Hours	0.02	0.30	0.45	0.46	0.43	0.34	0.04	0.35	0.54	0.60	0.60	0.52	0.04	0.10	0.24	0.26	0.26	0.21						
Investment	0.01	0.22	0.36	0.40	0.44	0.48	0.00	0.24	0.42	0.50	0.55	0.62	0.03	0.14	0.32	0.40	0.45	0.45						
Output	0.02	0.42	0.57	0.67	0.72	0.74	0.01	0.41	0.60	0.72	0.79	0.85	0.01	0.22	0.42	0.54	0.60	0.60						
Labor Productivity	0.00	0.10	0.11	0.20	0.33	0.60	0.00	0.06	0.06	0.11	0.21	0.45	0.00	0.15	0.20	0.31	0.43	0.59						

This table has two panels each of which reports the OLS point estimate of the share of forecast error variance attributable to (optimism/future TFP growth/news) shocks, which are identified by Sign Restrictions Method with Identification III, Max Share Method with the finite horizon (h) of 80 quarters, Barsky and Sims's Method with the truncation horizon (H) of 80 quarters, and Beaudry and Portier's Method that is available only for the five-variable system, for various forecast horizons. Panel A is the five-variable system with (BFK's Adjusted TFP, Stock Price, Consumption, Real Interest Rate, Hours) and Panel B is the seven-variable system with (BFK's Adjusted TFP, Stock Price, Consumption, Real Interest Rate, Hours, Investment, Output) where the forecast error variance share of Labor productivity is calculated from those of Output and Hours. The letter h refers to the forecast horizon.