Do mood swings drive business cycles and is it rational?*

Paul Beaudry†
University of British Columbia

Deokwoo Nam‡
Hanyang University

Jian Wang§
Federal Reserve Bank of Dallas

June 16, 2014

Abstract

We provide evidence that bouts of optimism and pessimism that are identified from stock price drive much of US business cycles. Using sign-restriction based identification schemes to isolate innovations in optimism or pessimism, we first 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. We find a very close link between the two. While this finding is consistent with some previous findings in the news shock literature, we cannot rule out that such episodes reflect self-fulfilling beliefs.

JEL Classification: E1, E3, G12

Keywords: Optimism shocks, sentiment shocks, expectation-driven business cycles and asset prices

*We thank Fabrice Collard, Andre Kurmann, Guido Lorenzoni, Barbara Rossi, Frank Portier, Henry Siu, Harald Uhlig, and participants at various seminars and conferences for helpful comments. All views are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Dallas or the Federal Reserve System.

†Email: paulbe@interchange.ubc.ca. Address: Department of Economics, University of British Columbia, 997-1873 East Mall, Vancouver, B.C., Canada, V6T 1Z1.

‡Email: deokwnam@hanyang.ac.kr. Address: Department of Economics and Finance, Hanyang University, 222 Wangsimni-ro, Seongdong-gu, Seoul, Korea, 133-791.

§Email: jian.wang@dal.frb.org. Address: Research Department, Federal Reserve Bank of Dallas, 2200 N. Pearl Street, Dallas, TX 75201.
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. The approach of expectation-driven business cycles is also useful to replicate stylized facts in financial markets. Hirshleifer and Yu (2013) reconcile stylized facts about business cycles and financial markets by introducing extrapolative expectations into a standard one-sector production-based real business cycle model. Examples of other recent studies on expectation-driven business cycles and financial markets include Gunn and Johri (2013) and Yu (2013).1

Within this tradition, however, 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.2 Closely related to this view, because of its shared rational basis, is the news view of mood swings.3 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.4

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.5 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 from stock prices 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

---

1Gunn and Johri (2013) generate boom-bust cycles in real output, asset prices, leverage and credit spread through changes in expectations on bankruptcy costs. Yu (2013) proposes an open-economy model in which the over- and under-estimate of home and foreign relative economic growth can account for the forward premium puzzle and other international business cycle puzzles.

2For example, see Benhabib and Farmer (1994) and Farmer and Guo (1994).

3For example, see Cochrane (1994a and 1994b), Beaudry and Portier (2004 and 2006), Jaimovich and Rebelo (2009), and Schmitt-Grohe and Uribe (2012).

4For example, see the book by Akerlof and Shiller (2009).

5Although there has been considerable empirical research on the roles of beliefs, news and animal spirits in business cycle fluctuations, there remains considerable disagreement about the results. For example, regarding the importance of news shocks, Barsky and Sims (2011 and 2012) 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 provide new evidence.
Barsky and Sims (2011). We then compare the identified shocks to future TFP growth with the 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 part of the paper will therefore begin by examining the relevance of optimism and pessimism 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 (SVAR) literature. They serve as an alternative to conventional “zero restrictions” to identify structural shocks and their associated impulse response functions. 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 driven by neither 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 current 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 account for over 40% 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.

\footnote{For example, see Dedola and Neri (2007), Peersman and Straub (2009), and Enders, Muller, and Scholl (2011).}
We also find that our identified optimism shocks replicate some well-documented business cycle properties in the US labor market. For instance, the optimism shocks account for more business cycle fluctuations in the unemployment rate (extensive margin) – over 40% of its forecast error variance at business cycle frequencies – than hours per worker (intensive margin) – around 10% of its forecast error variance. This is consistent with the fact that the extensive margin contributes to much of the variations in US total hours during business cycles, suggesting that the optimism shocks play an important role in US business cycles. In addition, our findings on other labor market variables such as the labor force participation rate, the job finding rate, the job separation rate, and job vacancy posting point to a similar story.

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 VAR system. 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 a recent paper, Arias et al. (2014) argue that the penalty function approach in Mountford and Uhlig (2009) is overly restrictive and may produce biased estimates and artificially narrow confidence intervals. They propose an alternative algorithm to address the problem. As can be seen in their paper, our main findings also hold well even under their method: the impulse response functions display similar patterns and are statistically significant for our benchmark sign restriction identification scheme (identification III), though the confidence intervals are wider under their method. The identified optimism shocks under this alternative method still account for about 40% of the FEV of consumption and 30% of the FEV of hours, which is lower than we find here, but which is still an important fraction of business cycle fluctuations.7

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

---

7These results are reported in Figure 4 and Table 12 of Arias et al. (2014).
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 (e.g., a measure of productivity) 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 the future TFP growth shock. 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 that given truncation horizon. Hence, these two methods differ in their treatments of short-run/temporary predictable 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. If we use a long forecast horizon (e.g., 80 quarters), we get very similar results regardless of using Francis et al.’s method or Barsky and Sims’ method. The identified future TFP growth shocks are highly correlated with the optimism shocks identified from the sign restrictions method. The identified future TFP growth 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. However, if we use a shorter horizon (e.g., 40 quarters), we get a different picture. In this later case, the impulse responses to the predictable TFP growth shocks identified from Barsky and Sims’ (2011) method are different from those to the optimism shocks. For example, the future TFP growth shocks are associated with an initial decline in hours worked and output and TFP increases on impact of the shock, while this is not the case

---

8See Faust (1998) and Uhlig (2004) for earlier studies similar in spirit to the maximum forecast error variance methods in Francis et al. (2005) and Barsky and Sims (2011).

9The 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 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 (see Kurmann and Mertens, forthcoming).

10Barsky and Sims (2011) use the forecast horizon of 40 quarters in their study.
for the optimism shocks identified from sign restrictions. The results for Francis et al.’s method are less sensitive to the choice of forecast horizon than those for Barsky and Sims’ method. As we discuss later, this discrepancy may result from different treatments of transitory 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. It is reasonable for macroeconomic variables such as consumption to rise when future TFP is expected to increase. However, our empirical exercise cannot evaluate if the changes in macroeconomic variables are quantitatively optimal.

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 total hours or other labor input measures such as unemployment, the job finding rate and job vacancy posting 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 each of these labor input measures at business cycle frequencies has a structural interpretation, it is astonishing to see how closely it mimics our optimism shock or 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 (and other labor input measures) 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 shocks induce dynamics that are somewhat different from standard accounts of macroeconomic 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 2012). 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. We will then highlight the source and potential explanations of these differences later in the paper.

The remainder of the paper is arranged as follows. Section 2 describes our sign restrictions strategies to identify optimism shocks and presents implications of identified optimism shocks. Section 3 introduces the maximum forecast error variance methods used to identify future TFP growth shocks. In Section 4, we compare identified optimism shocks with identified future TFP growth shocks to provide their links, examine the properties of the shocks that best explain business cycle fluctuations in several labor input measures, and discuss the related 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 those 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 (ignoring
a constant term for simplicity):

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

where \( Y_t \) is an \( n \times 1 \) vector of variables in levels, \( \Phi_k \) is reduced-form VAR coefficient matrix, and \( u_t \) is reduced-form innovations with the variance-covariance matrix denoted by \( \Sigma_u \). The reduced-form moving-average representation is expressed as:

\[ Y_t = \sum_{h=0}^{\infty} B(h) u_{t-h}, \]  

(1)

where \( B(0) = I \) is an identity matrix. The first assumption is that there is a linear mapping between reduced-form innovations \( u_t \) and economically meaningful structural shocks \( \epsilon_t \):

\[ u_t = A_0 \epsilon_t, \]  

(2)

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

\[ A_0 = \tilde{A}_0 Q, \]  

(3)

where \( \tilde{A}_0 \) is any arbitrary orthogonalization of \( \Sigma_u \) (e.g., Cholesky decomposition of \( \Sigma_u \)) and \( Q \) is an orthonormal matrix (i.e., \( QQ' = I \)). The identification of structural shocks \( \epsilon_t \) (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:

\[ Y_t = \sum_{h=0}^{\infty} R(h) \epsilon_{t-h}, \]  

(4)

where \( R(h) = C(h) Q \) with \( C(h) = B(h) \tilde{A}_0 \). So the impulse response vector of variables to a structural shock that corresponds to the \( j^{th} \) element of \( \epsilon_t \) 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 $r^{(j)}_i(h)$:

$$r^{(j)}_i(h) = C_i(h) q^{(j)},$$

(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 $h = h_i, \ldots, \overline{h}_i$, 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:

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

(6)

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

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

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 $h_i$ to horizon $\overline{h}_i$ following a structural shock of interest (e.g., an optimism shock in our study). $\sigma_i$ is the standard error of variable $i$ and the impulse response is re-scaled by $\sigma_i$ 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 that have immediate impact on a measure of TFP. This corresponds to imposing a zero restriction on the impact impulse response of TFP following an optimism shock. In the penalty-function approach, such zero restriction can be easily incorporated. 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:

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

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 stereographic projection. This can be summarized as follows. First, we take a draw from the Normal-Wishart posterior for $(\Phi, \Sigma_u)$ 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.\(^{11}\) Then, statistical inferences (e.g., confidence intervals of impulse responses) are based on the distribution of those draws that solve equation (7).

### 2.2 Data and Sign Restrictions Strategies

In our empirical studies, we use quarterly US data of the sample period from 1955Q1 to 2012Q4. The starting and ending dates of our sample are dictated by the availability of the data.\(^{12}\) Our dataset contains the following variables: TFP, stock price, consumption, investment, output, hours worked, the real interest rate, the inflation rate, the real wage, consumer confidence and real inventories. To make a deeper understanding of the role of optimism shocks in the labor market, we also consider the following labor input variables: the unemployment rate, hours per worker, the labor force participation rate, the job finding rate, the job separation rate and job vacancies.\(^{13}\)

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.\(^{14}\) We also report some results using a

\(^{11}\) 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 $\gamma$, on the plane, and then project $\gamma$ on the unit sphere to obtain an $n \times 1$ unit vector $q$ that also satisfies the zero restriction in equation (7).

\(^{12}\) The federal funds rate that is used to calculate the real interest rate starts in 1955Q1. The factor-utilization-adjusted TFP series ends in 2012Q4. The results reported in this paper are robust to the sample period from 1955Q1 to 2007Q4, which excludes the recent global financial crisis.

\(^{13}\) We thank the referee for recommending us to extend our paper in this direction.

\(^{14}\) Our (adjusted and non-adjusted) TFP series are obtained from the website of John Fernald. We also use adjusted TFP
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.\textsuperscript{15}

Our stock price measure is the end-of-period Standard and Poor’s 500 composite index (obtained from the \textit{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 the sum of real gross private domestic investment and real durable goods, which are obtained 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 into 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 real wage is measured by non-farm business hourly compensation from the BLS divided by the GDP deflator from the BEA. Our measure of inventories is real non-farm private inventories from the BLS divided by the population. 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 unemployment or depression, or what?” We use E5Y to denote this measure of consumer confidence. As robustness checks, we also consider the 12-month ahead expectation in the University of Michigan Survey (denoted by E12M) and the index of expectations of the Conference Board as our alternative measures of consumer confidence.\textsuperscript{16}

For the labor market variables, the labor force participation rate and the unemployment rate are obtained from the BLS. The hours per worker is calculated from non-farm payrolls aggregate hours and civilian employment obtained from the BLS. The job finding and separation rates are calculated from seasonally

\textsuperscript{15}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 to TFP – which are one interpretation of the optimism shocks we examine here.

\textsuperscript{16}The Survey of Consumers data starts in 1960Q1 and the Conference Board data starts in 1967Q1.
adjusted employment, unemployment, and mean unemployment duration data from the BLS, following Shimer (2005). Job vacancies are measured by the help wanted index (HWI) in Barnichon (2010).\footnote{We thank Regis Barnichon for providing the latest HWI data.}

In our benchmark VAR model, $Y_t$ contains seven variables ($n = 7$): TFP, stock price, consumption, the real interest rate, hours worked, investment, and output. All variables are logged except for the real interest rate and enter the system in levels. 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 price 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 price 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.\footnote{Our results are robust to excluding the zero restriction on the impact response of TFP.} 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, that is, on impact. 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 price. 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. However, the main focus of their study is only on 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
argument that agents may have advance information about future economic conditions that they use when making consumption decisions.

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 sequentially 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 or smaller VAR systems than our benchmark seven-variable system. In all alternative systems, we still use the same sets of sign restrictions as in the seven-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 System

Figure 1 displays the impulse responses to a unit identified optimism shock in our benchmark seven-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 price rises on impact and TFP does not change. This is by construction as they are the identifying restrictions. Interestingly, consumption rises and the real interest rate does not decline immediately following the identified 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. Investment and output display a similar hump-shaped pattern as hours worked. Furthermore, the responses of consumption, investment, and output are quite persistent. Note that consumption, hours, investment, and output rise substantially above zero and reach their peaks before TFP starts to rise above zero. All of these responses suggest that we may be isolating an optimism shock.

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.
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 are followed by changes in fundamentals. These findings are very similar to Beaudry and Portier (2006), suggesting that innovations in stock price 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 new long-run level. Hours reach a higher peak and TFP converges to a higher long-run level in Identification II when compared to Identification I. Finally, investment and output also reach their higher peaks and converge to their new long-run levels. That is, the positive restriction on consumption helps to identify optimism shocks that have permanent effects on macroeconomic variables. 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.\(^{19}\) Although the positive impact restriction on the real interest rate makes the short- to medium-term responses of hours, investment, and output less amplified, the long-run effect of the identified optimism shocks on TFP, consumption, investment, and output become more pronounced. This finding indicates that the sign restriction on the real interest rate in Identification III helps to exclude the transitory effects of expansionary monetary policy and pick up the optimism shocks with permanent effects more precisely.

Figure 2 presents the impulse responses of the alternative seven-variable system, in which non-adjusted TFP is used as the first variable. Overall, the impulse responses are similar to those in the benchmark seven-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

\(^{19}\)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.
the eventual permanent rise of TFP is about ten quarters no matter if we use adjusted or non-adjusted TFP. 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.

Panel A of Table 2 reports the share of the forecast error variance (FEV) of each variable that is attributable to optimism shocks in the benchmark seven-variable system. Three panels of Panel A report the results under three sets of sign restrictions, 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 III, optimism shocks account for more than 50% of the FEVs of consumption and output and about 40% of the FEVs of hours and investment at horizons 8 to 40 quarters. Around 25% of the FEV of TFP at the horizon of 40 quarters is explained by optimism shocks. The results of FEV decomposition using non-adjusted TFP are qualitatively similar. To save space, we do not report them here. There is only one noticeable difference. 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, as implied by their estimated impulse responses.

2.3.2 Results of Labor Market Variables and Robustness Checks

We now check the robustness of our findings in different subsample periods and also in cases using different measures of labor market conditions and consumer confidence and other variables of interest such as the inflation rate. All the results are presented in Figure 3. The left panel of Figure 3 displays the median impulse responses in two subsamples as well as in the full sample when optimism shocks are identified with Identification III. The results are qualitatively similar when the other two identification strategies in Table 1 are employed. The pre-1978 subsample covers the period from 1955Q1 to 1978Q4 (the line with squares). The post-1983 subsample covers the period from 1983Q1 to 2012Q4 (the line with triangles). The full sample ranges from 1955Q1 to 2012Q4 (the line with circles). 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).

The left panel of Figure 3 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. However, 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 since the mid 1980s after inflation came under control.

The middle panel of Figure 3 presents our results for a group of labor market variables. A further investigation on these variables suggest that our findings on the optimism shocks are generally consistent with business cycle features of US labor market, supporting that our identified optimism shocks play an important role in driving US business cycles. In these exercises, total hours in the benchmark seven-variable model are replaced by each of the following labor input variables: hours per worker, the unemployment rate, the labor force participation rate, the job finding rate, the job separation rate, job vacancies, and the ratio of job vacancies to unemployment. In these seven-variable systems with one of the above labor input variables, optimism shocks are identified under Identification III in Table 1, in which the impulse response of the labor input variable is unrestricted. In the panel, we only report the impulse responses of labor input variables since the responses of other six variables are almost identical to our benchmark results in Figure 1.

Several interesting findings stand out. First, hours per worker rises immediately following the optimism shock, but its response is much temporary and smaller than that of total hours following an optimism shock – the identified optimism shocks account for only around 10% of the forecast error variance of hours per worker at business cycle frequencies. It indicates that the intensive margin (hours per worker) explains only a limited fraction (about 30%) of total hours fluctuations following an optimism shock, which is consistent with previous empirical studies on US business cycles. For example, Cho and Cooley (1994) document that only a quarter of the adjustment in total hours of employment over the business cycle is through adjustment in hours in the US, while the remainder is through changes in employment. On the other hand, the identified optimism shocks have a substantial effect on the unemployment rate and its response mirrors the response of total hours – the identified optimism shocks explain more than 40% of the forecast error variance of the unemployment rate at business cycle frequencies. In addition, the optimism shock is not found to have significant effect on the labor force participation rate. The responses of all these four labor input measures

---

See Figures 5 and 6 for the impulse responses of all variables in the seven-variable system with each labor input variable to an optimism shock.

More recently, Ohanian and Raffo (2012) compare the US with other major advanced economies. They find that a large fraction of labor adjustment takes place along the intensive margin in other countries, though it does not in the US.

Instead of the unemployment rate, we also use unemployment in levels as a measure of unemployment, and the result is almost the same as in the case of the unemployment rate.
suggest that changes in total hours are mainly due to changes in employment (extensive margin).

We also investigate if the effect of our identified optimism shocks on the unemployment rate is consistent with empirical findings in the business cycle literature. In the third row of the panel, we document that the job finding rate responds strongly to the optimism shock while the job separation rate changes only slightly following the shock – the identified optimism shocks are found to account for around 45% and 20% of the forecast error variances of the job finding and separation rates at business cycle frequencies, respectively. This result is consistent with Shimer’s (2012) finding that the job finding rate accounts for over 75% of the fluctuations in the US unemployment rate. In addition, we show in the last row of the panel that an increase in the job finding rate following an optimism shock is accompanied with a strong increase in job vacancies, suggesting that the increase in the job finding rate is due to the job creation – following the optimism shock, a sharp rise in job vacancies strongly increases the ratio of job vacancies to unemployment that increases the possibility of finding a job.

The right panel of Figure 3 displays the impulse responses of the real wage, the inflation rate, real inventories, and three measures of consumer confidence to an optimism shock identified in eight-variable systems. Each of them is obtained by adding one of these variables to the benchmark system, and then optimism shocks are identified under Identification III except for the case of the inflation rate. The first aspect to note is that the addition of a new variable does not change any of the findings from the benchmark seven-variable system. Therefore, we can focus exclusively on the properties of the added variable. In the first exercise, the real wage is added to the seven-variable system. Following an optimism shock, the real wage increases gradually and converges to a permanently higher level. We also checked two alternative measures of the real wage: real hourly earnings for goods producing industries and that for manufacturing. Both variables are deflated by the CPI for urban wage earners and clerical workers (CPI-W) and obtained from the BLS. Our results are robust to these alternative measures of the real wage with different deflators. These findings suggest 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.

We next 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 as in identification III. The interesting finding from this panel is that inflation almost does not change in response to our identified optimism shock.

When real inventories are considered, they increase gradually following the identified optimism shock, peak before TFP increases above zero, and then converge to their new long-run level. Since the identified
optimism shock is important for U.S. business cycles, this finding is consistent with the fact that inventories are usually pro-cyclical in the data. Crouzet and Oh (2014) show that a positive news shock in standard inventory business cycle models induces a decline in inventories. This discrepancy between the theoretical models and the data deserves further investigation in the future, casting doubt on the transmission mechanism of news shocks (one interpretation of our identified optimism shocks) in standard inventory models.

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 each of three survey measures of consumer confidence to our benchmark system to examine whether our optimism shocks are also reflected in such surveys. The right panel of Figure 3 shows the impulse responses to an optimism shock when we add a measure of consumer confidence from the Survey of Consumers of the University of Michigan (denoted by E5Y and E12M) or from Conference Board. The panel indicates that following an identified optimism shock, different measures of consumer confidence display a similar pattern – rising strongly on impact and exhibiting a persistent decline over time. In addition, we find that optimism shocks account for a large fraction of the forecast error variance of these confidence measures. This finding is consistent with Barsky and Sims (2011), suggesting that the measures of consumer confidence are closely related to our notion of optimism.

In a robustness check, we show in the seven-variable system that removing the zero restriction on the impact impulse response of 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 corresponding cases with the zero restriction on TFP. We also show that our findings are robust in a smaller (five-variable) system after removing investment and output form the seven-variable benchmark model, using either utilization-adjusted or non-adjusted TFP.\textsuperscript{23}

We confirm in these alternative systems that optimism shocks remain important in driving business cycle fluctuations of macroeconomic variables. For instance, optimism shocks usually account for around 40% of the FEVs of hours and investment and more than 50% of the FEVs of consumption and 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

\textsuperscript{23}The results of these robustness checks can be found in the working paper version of the current paper (Beaudry, Nam, and Wang, 2011).
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 briefly introduce two methods used to identify what we will call future TFP growth shocks, and then implement these methods in the seven-variable systems studied previously. 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 growth 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, which will be our main focus in the next section.

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:

\[
\Omega_1 (h) = q' F_1 (h) q,
\]

where \( F_1 (h) \) is an \( n \times n \) positive-definite, symmetric matrix:

\[
F_1 (h) = \left( \sum_{k=0}^{h} C_1 (k)' C_1 (k) \right) / \left( \sum_{k=0}^{h} C_1 (k) C_1 (k)' \right).
\]
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.\(^{24}\) 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 \((h)\), then we can identify such a shock by solving the following maximization problem given the Cholesky decomposition of \(\Sigma_u\), \(\tilde{A}_0\):

\[
q^* = \arg \max_q \Omega_1 (h), \quad s.t. \quad (1) \quad q'q = 1; \quad (2) \quad q_1 = 0,
\]

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.\(^{25}\)

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

\(^{24}\)The max share identification assumption essentially allows other shocks to influence technology at all finite horizons over which the max share algorithm is employed.

\(^{25}\)The impact response of TFP is \(C_1 (0) q = \tilde{A}_0 (1,:) q\), where \(\tilde{A}_0 (1,:)\) is the first row of \(\tilde{A}_0\). Given the Cholesky decomposition of \(\Sigma_u\) (i.e., \(\tilde{A}_0 (1,1) \neq 0\) and \(\tilde{A}_0 (1,j) = 0\) for \(j > 1\)), the zero restriction that the impact response of TFP is zero (i.e., \(\tilde{A}_0 (1,:) q = 0\)) collapses to \(q_1 = 0\).
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 \( \Sigma_u, \tilde{A}_0 \):  

\[
q^* = \arg \max_q \sum_{h=0}^{H} \Omega_1 (h), \quad \text{s.t.} \quad (1) \quad q'q = 1; \quad (2) \quad q_1 = 0,
\]

where \( \sum_{h=0}^{H} \Omega_1 (h) = q' F_1 (H) q \) is the sum of the shares of the FEV of TFP attributable to future TFP shocks over a finite subset of horizons and \( F_1 (H) = \sum_{h=0}^{H} F_1 (h) \). 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 max share method identifies a shock that influences TFP at horizon \( h \), but allows other shocks such as measurement errors to influence TFP over most other horizons. When \( h \) is set to a large number such as 60 or 80 quarters, the identified shocks drive TFP in the long run and other shocks are allowed to influence TFP in the short and medium run. In contrast, Barsky and Sims’ method minimizes the influence of other shocks on TFP for all horizons up to the truncation horizon \( H \). In this way, their method are more likely to contaminate the effects of future (news) TFP shocks by capturing other shocks to short- and medium-run movements in TFP.

The relevant Lagrange problems for the maximization problems in equations (10) and (11) imply that the solution takes the form: \( q^* = \left( \begin{array}{c} 0 \\ q^*_{(2)} \end{array} \right) \), 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 \( F_1 (h) \) in the max share method, or a \((n - 1) \times (n - 1)\) sub-matrix of \( F_1 (H) \) in Barsky and Sims’ method. The sub-matrix is obtained by eliminating the first row and the first column of \( F_1 (h) \) or \( F_1 (H) \). 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 under different values of \( h \) and \( H \).  

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. 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.
3.2 Results of Future TFP Growth Shocks

In Figure 4, the first two panels present the impulse responses to a future TFP growth shock identified by the max share and Barsky and Sims’ methods in our benchmark seven-variable model, respectively. We consider three different values of the finite horizon \( h \) in the max share method and the truncation horizon \( H \) in Barsky and Sims’ method: 40, 60, and 80 quarters. The black line with circles, the blue line with triangles, and the red line with squares correspond to the median impulse responses for the horizon \((h \text{ or } H)\) of 40, 60, and 80 quarters, respectively. The shaded gray area represents the confidence interval with the 16th and 84th quantiles for the horizon of 40 quarters.

Under the max share method, TFP does not rise above zero until about eight quarters for all choices of horizon \( h \). 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 hours and output are a little sensitive to the value of the finite horizon \( h \). When \( h \) is set to 40 quarters, hours and output decline very slightly on impact of a future TFP growth shock. In contrast, when \( h \) is set to 60 or 80 quarters, these three variables do not change or slightly increase on impact in response to a future TFP shock. As expected, the permanent effect of the future TFP growth shock becomes stronger as the finite horizon \( h \) gets larger. In sum, the impulse responses of variables to the long-run future TFP growth shock (\( h \) is set to a relatively large value in the max share method) is robust.

The middle panel of Figure 4 displays the impulse responses following the shock that is identified by Barsky and Sims’ method with varying \( H \). The results of the max share method and Barsky and Sims’ method 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 \( h \).

Even for long horizons, hours and output are still below zero on impact when using Barsky and Sims’ method as compared to the max share method. Moreover, TFP in Barsky and Sims’ method 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 and output, while TFP rises immediately after the impact of the identified shock.

Panel B of Table 2 reports the share of the forecast error variance (FEV) attributable to future TFP growth shocks identified by the max share or Barsky and Sims’ method. Identified future TFP growth shocks...
account for more than 50% of the FEVs of consumption and output and over 40% of the FEVs of hours and investment at horizons 8 to 40 quarters. Around 40% of the FEV of TFP at the horizon of 40 quarters is explained by future TFP growth shocks.

4 Links between Optimism-driven Fluctuations and Fundamentals

In this section, we first show that the optimism shocks identified using sign restrictions are closely linked to future TFP growth shocks identified using the max share method or Barsky and Sims’ method. 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. Thus, 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. We next show that the shocks that best explain business cycle fluctuations in major labor input measures have the properties of our identified optimism shocks. This finding can corroborate the importance of optimism shocks in driving business cycles. Finally, we discuss the related literature.

4.1 Optimism Shocks and Future TFP Growth Shocks are Closely Linked

The right panel of Figure 4 displays the impulse responses to a unit shock identified by the sign restrictions method with Identification III (the line with circles), the max share method with the finite horizon of 80 quarters (the line with triangles), or Barsky and Sims’ method with the truncation horizon of 80 quarters (the line with squares). Although the algorithms for identifying the shocks in these three methods are very different, the impulse responses of all variables are very close across these methods. We calculate the correlations between the identified shocks from different methods. Shocks identified from these methods are highly correlated: in particular, the correlation between optimism shocks identified from sign restrictions and the shocks identified from the max share method is 0.84 and the correlation between the identified optimism shocks and the shocks identified from Barsky and Sims’ method is 0.79.\footnote{In the working paper version of this paper (Beaudry, Nam, and Wang, 2011), we also consider the five-variable system obtained by removing investment and output, and then implement 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 vector error correction model (VECM). We find that the impulse responses are almost identical for all variables obtained from these four methods and that the shocks identified from all methods are almost perfectly correlated: the correlation is 0.90 or higher in all cases.} 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 highly correlated suggests that the initial changes in sentiment either contain substantial news about future productivity, or somehow cause future productivity growth.

As reported in Table 2, shocks identified from different methods perform similarly in the forecast error variance (FEV) decomposition. These shocks explain only a small fraction of the FEV of TFP at horizons of 16 quarters or less, but a significant fraction at a horizon of 40 quarters. The shocks account for more than 50% of the FEV of consumption and close to 40% of the FEV of hours at business cycle frequencies under all methods. 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 developments 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.

4.2 Similarity between Optimism Shocks and Shocks that Best Explain Business Cycle Fluctuations in Labor Input Measures

Given the importance of our identified optimism shocks in explaining movements in hours worked and other labor input measures at business cycle frequencies and the important role of labor market in US business cycles, we pursue our analysis by asking the question: if we looked for a shock that best explains business cycle fluctuations in a labor input variable of interest, would this shock look like bouts of optimism and pessimism? To explore this issue, we use the (modified) max share method to identify a shock that maximizes the forecast error variance of a labor input variable at the horizons from 6 to 32 quarters. This exercise is closely related to one performed by Uhlig (2003) for GDP. Then we compare the identified shock with the optimism shock identified from our sign restrictions schemes.

In Figure 5, the three panels present the median impulse responses to shocks that maximize their contributions to business cycle fluctuations in total hours, hours per worker, and the unemployment rate, respectively. When identifying such shocks, the zero impact restriction on TFP is imposed (represented by the line with triangles) or not (represented by the line with squares). For the purpose of comparison, we also plot the median impulse response and the confidence interval to a unit optimism shock identified by imposing sign

30There is one exception. Under Barsky and Sims’ method, 16% of the FEV of TFP at horizon 16 quarters is attributable to the identified shocks.
restrictions of Identification II in Table 1. The line with circles represents the median response and the shaded gray area is the confidence interval with the 16th and 84th quantiles.

We first see in the right panel of Figure 5 that the shock that maximizes its contribution to business cycle fluctuations in the unemployment rate has almost identical impulse responses as the optimism shock, which indicates these two shocks are highly correlated. The identified shock accounts for more than 70% of the FEV of the unemployment rate at business cycle frequencies and generates dynamics that can easily be interpreted as reflecting optimism. Similar results are also found for total hours. These results suggest that most of what we observe as business cycle fluctuations of hours worked and the unemployment rate 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, the optimism shocks may either have a self-fulfilling component or reflect news.

In contrast, the impulse responses to the shock that maximizes business cycle fluctuations in hours per worker differ significantly from those to the optimism shock, confirming that the optimism shock only plays a moderate role in driving hours per worker at business cycle frequencies. This finding is intuitive: if the optimism shock is important for business cycle variations in total hours worked and the intensive margin (i.e., hours per worker) only accounts for a moderate fraction of fluctuations in total hours worked, the shock that drives hours per worker should behave differently from the shock that drives total hours, which is found to resemble the optimism shock.

In Figure 6, we find similar results for the job finding rate, job vacancies, and the job separation rate. The shock that maximizes its contribution to business cycle variations in the job finding rate and job vacancies have very similar impulse responses as the optimism shock, suggesting that optimism shock is important in driving the job finding rate and job vacancies. However, this is not true for the case of the job separation rate, indicating the optimism shock is not a main driving force of the job separation rate. This finding is consistent with the fact that job separation only accounts for a small fraction of business cycle fluctuations in the unemployment rate and the optimism shock is important in driving the unemployment rate.31

4.3 Discussion of the Related Literature

We finish this section by discussing the relationship between this paper, Barsky and Sims (2011 and 2012) and Beaudry and Portier (2006). This comparison helps to understand some conflicting results in the literature. Table 3 summaries some differences among these studies. First, the shocks that are identified in these studies

31To save space, we do not report the results of the shock that maximizes its contribution to the forecast error variance of the labor force participation rate. The impulse responses to that shock are totally different from those to the optimism shock, as implied by the impulse response of the labor force participation rate to our optimism shock in the middle panel of Figure 3.
are different, though all of them are labelled as news or confidence/optimism shocks. Beaudry and Portier (2006) identify an optimism shock reflected in stock prices. They interpret the identified optimism shock as news about future TFP because they find that the optimism shock is closely linked to long-run TFP shocks.

Our study follows a similar idea in Beaudry and Portier (2006), but the sign restrictions method implemented in this paper can be applied to much larger VAR systems than those in Beaudry and Portier (2006). As a result, we can investigate the effects of optimism shocks on business cycles more broadly. For instance, we examine various measures in the labor market and confirm that the optimism shocks display well-documented labor market properties during business cycles. In addition, the max share method introduced in this paper is also more flexible than the long-run restrictions method in Beaudry and Portier (2006) and allow us to compare our findings more closely with other previous results.

Barsky and Sims’ (2011) method is related to the max share method, as we discussed before. Both methods identify shocks that influence future TFP, but on impact have no effect on TFP. However, these two methods identify different news to future TFP. It is clear in section 3.1 that Barsky and Sims’ method identifies news shocks to short- and medium-run TFP movements as well as long-run TFP movements, but news shocks identified from the max share method are more likely to contain news to relatively long-run TFP movements. By comparing these identified news TFP shocks with optimism shocks identified from the sign restrictions method and Beaudry and Portier’s (2006) method, we know that the optimism shocks are more closely linked to news to long-run TFP movements. This observation reconciles two discrepancies between this paper and Barsky and Sims (2011). First, the shocks in this paper affect TFP with a longer lag than the shocks in Barsky and Sims (2011) since their shocks contain news to short- and medium-run future TFP movements. Second, Barsky and Sims’ identified shocks are less important than ours in driving US business cycles. It is reasonable that agents react to news about long-run movements in TFP, rather than news about short-run and transitory movements.

Our results in this paper 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

---

32 When applied to large VAR systems, Beaudry and Portier’s (2006) method has to impose short-run zero restrictions that are difficult to justify. In particular, Kurmann and Mertens (forthcoming) show that Beaudry and Portier’s (2006) identification scheme does not have a unique solution when applying to VECMs with more than two variables due to a particular interplay of cointegration assumptions and long-run restrictions.

33 We also examine how sectoral components of TFP relate to our identified optimism shocks. We find that (i) our identified optimism shocks precede substantial long-run increases in investment-sector TFP, while consumption-sector TFP does not increase substantially following the identified optimism shock, and (ii) the shocks that maximize predictable changes in investment-sector TFP resemble very closely our optimism shocks, while this is not the case for consumption-sector TFP. It suggests that the shocks to long-run aggregate TFP growth may reflect news about long-run changes in investment-sector TFP. These results are reported in the appendix available on the authors’ websites.

25
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 that causes booms.

Unlike the above studies, Barsky and Sims (2012) do not use a SVAR approach. Instead, they use measures of consumer confidence from the Michigan survey within the confines of a structural dynamic stochastic general equilibrium (DSGE) model to explore similar issues to those of the current paper. In particular, Barsky and Sims (2012) 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 (2012) 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. Barsky and Sims (2012) assume 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. This assumption is drawn on empirical findings in Barsky and Sims (2011). 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). An interesting aspect of this pattern is that it is qualitatively 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’ (2012) 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. For example, their

---

34 Barsky and Sims (2011) emphasize that news shocks appear to cause a fall in hours until TFP starts increasing.
35 Barsky and Sims (2012) 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.
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.\textsuperscript{36} 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 7 we report three sets of results based on our five-variable system, where we simply replace stock prices with the consumer confidence index used by Barsky and Sims (and described in Section 2.2).\textsuperscript{37} The first four panels report impulse responses to optimism/confidence shocks identified by imposing sign restrictions of Identifications I and II: in the first two panels, the zero impact restriction on TFP is not imposed and the restriction is imposed in the following two panels. In the last panel, the impulse responses to a future TFP growth shock are reported, where the future TFP shock is identified by applying the max share method with the horizon of 80 quarters. In each of the five panels, the line with squares represents the median response and the shaded gray area represents the confidence interval with the 16th and 84th quantiles. For the purpose of comparison, the corresponding median impulse responses estimated in the five-variable system with stock prices (the line with triangles) are also plotted.

There are two main observations from Figure 7 we want to emphasize. First, if we look at the first and third panels, we observe a pattern that is generally consistent with the view proposed by Barsky and Sims (2011 and 2012) 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, which is more pronounced in the first panel where the zero impact restriction on TFP is not imposed (here we can also compare the responses in the system with consumer confidence (the

\textsuperscript{36}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.”

\textsuperscript{37}Using the seven-variable system gives similar results.
line with circles) with those in the system with stock price (the line with triangles)). Hence, as argued by Barsky and Sims (2012), these observed patterns for consumption and hours can be rather easily explained by standard mechanisms. Although Barsky and Sims (2012) do not use a SVAR approach to make their case, this figure captures the crux of their narrative. However, if we look at the second, fourth, and fifth 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 that peaks at a time when TFP has virtually not yet started to rise. Accordingly, these three panels (i.e., the second, fourth, and fifth ones) present an expansion that 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 three panels closely mimic the main results we reported in the two previous sections. Accordingly, the question becomes whether the observations from the first or third 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/third 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/third 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, it paints a picture of how optimism affects economic activity similar to that obtained from using stock prices alone (here we compare the lines with circles and the line with triangles in the first/third panel of Figure 7). 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. Suppose that survey participants respond survey questions based on observed stock price and consumption data as well as some other noises. When the noise is large enough, imposing restriction only on confidence survey data is not able to recover the optimism shocks that drive stock prices and consumption decisions. Combining consumer confidence with consumption data, as shown in the second/fourth panel of Figure 7, would help to filter out noises and better identify optimism shocks. While we can quite easily reproduce the results of Barsky and Sims (2011 and 2012), 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 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 (or other labor input measures such as unemployment, the job finding rate, and job vacancies), 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 (2011 and 2012), which pursue a similar issue using a different methodology.\footnote{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.}

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.\footnote{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, we documented in Section 4.2 that the shock that maximizes its contribution to the forecast error variance of hours worked or other labor input measures such as the unemployment rate, the job finding rate, and job vacancies 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 more than 70% of the variance of each of these labor input measure at the horizons from 6 to 32 quarters, 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 70% of the forecast error variance of hours or other main labor input measures 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.}

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. 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 precede eventual rises in TFP. We examined whether such shocks are correlated with our identified optimism shocks. We find that the two types of shocks are highly correlated suggesting that predictable and permanent increases in TFP are preceded by a boom period, and that bouts of optimism are followed by an eventual rise in TFP. The relationship is strong, so 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.
References


Figure 1: Impulse Responses to an Optimism Shock in the Benchmark Seven-variable System

**Sign Restrictions: Identification I**

- Adjusted TFP
- Stock Price
- Consumption
- Real Interest Rate
- Hours
- Investment
- Output

**Sign Restrictions: Identification II**

- Adjusted TFP
- Stock Price
- Consumption
- Real Interest Rate
- Hours
- Investment
- Output

**Sign Restrictions: Identification III**

- Adjusted TFP
- Stock Price
- Consumption
- Real Interest Rate
- Hours
- Investment
- Output

Notes: This figure has three panels each of which displays impulse responses to a unit optimism shock identified by imposing each of three sign restrictions that are described in Table 1 in the benchmark seven-variable system: Identification I (left panel), Identification II (middle panel), and Identification III (right panel). The green line with circles represents the median response and the shaded gray area represents the confidence band with the 16th and 84th quantiles. The unit of the vertical axis is percentage deviation from the situation without the shock and the unit of the horizontal axis is quarter.
Figure 2: Impulse Responses to an Optimism Shock in the Seven-variable System with Non-adjusted TFP in Place of Adjusted TFP

Sign Restrictions: Identification I

Sign Restrictions: Identification II

Sign Restrictions: Identification III

Notes: This figure has three panels each of which displays impulse responses to a unit optimism shock identified by imposing each of three sign restrictions that are described in Table 1 in the seven-variable system with non-adjusted TFP in place of adjusted TFP: Identification I (left panel), Identification II (middle panel), and Identification III (right panel). The green line with circles represents the median response and the shaded gray area represents the confidence interval with the 16th and 84th quantiles. The unit of the vertical axis is percentage deviation from the situation without the shock and the unit of the horizontal axis is quarter.
Notes: All of three panels of this figure display impulse responses to a unit optimism shock identified by imposing sign restrictions of Identification III except for the impulse response of the inflation rate in the right panel that is estimated by imposing Identification II. The left panel displays impulse responses in the benchmark system in either the pre-1978 subsample period from 1955:Q1 to 1978:Q4 (the line with squares represents the median response), the post-1983 subsample period from 1983:Q1 to 2012:Q4 (the line with triangles represents the median response), or the full sample period from 1955:Q1 to 2012:Q4 (the line with circles represents the median response and the shaded area represents the confidence interval with the 16th and 84th quantiles). The middle panel shows impulse responses of eight labor input measures in seven-variable systems with each labor input measure in place of (total) hours in the benchmark system. The right panel displays impulse responses of real wages, inflation, real private inventories, and three consumer confidence measures (expected business conditions in 5 years (E5Y), expected business condition in 12 months (E12M) in Surveys of Consumers by the University of Michigan and the consumer confidence index of Conference Board) in eight-variable systems that are obtained by adding each of those variables to the benchmark system. The unit of the vertical axis is percentage deviation from the situation without the shock and the unit of the horizontal axis is quarter.
Figure 4: Impulse Responses to a Future TFP Growth Shock in the Benchmark Seven-variable System

Max Share Method

Barsky and Sims Method

Comparison across Different Methods

Notes: The left and middle panels display the median impulse responses to a unit future TFP growth shock identified by Max Share method with the finite horizon \( h \) equal to 40, 60 or 80 quarters and Barsky and Sims method with the truncation horizon \( H \) equal to 40, 60 or 80 quarters, respectively. In each of these two panels, the black line with circles, the blue line with triangles, and the red line with squares correspond to the median impulse responses for the horizon of 40, 60, and 80 quarters, respectively, and the shaded gray area represents the confidence interval with the 16th and 84th quantiles for the horizon of 40 quarters. The right panel displays the OLS estimates of the impulse responses to a unit shock identified by the sign restrictions method with Identification III (the line with circles), the Max Share method with the finite horizon of 80 quarters (the line with triangles), or Barsky and Sims method with the truncation horizon of 80 quarters (the line with squares).
Figure 5: Impulse Responses to a Shock that Maximizes its Contribution to Business Cycle Fluctuations of Labor Input Measures

Notes: Each panel of this figure displays the median impulse response to a unit shock identified by applying the (modified) Max Share method to each labor input measure in the seven-variable system with that labor input: that is, the shock is identified by maximizing its contributions to the forecast error variance of that labor input measure at the horizons between 6 and 32 quarters, with the zero impact restriction on TFP (the line with triangles) or without the zero impact restriction on TFP (the line with squares). For the purpose of comparison, the median impulse response to a unit optimism shock identified by imposing sign restrictions of Identification II and its confidence interval are also plotted. The green line with circles represents the median response and the gray area is the confidence interval with the 16th and 84th quantiles.
Figure 6: Impulse Responses to a Shock that Maximizes its Contribution to Business Cycle Fluctuations of Labor Input Measures - Continued

Notes: See the notes below Figure 5.
Figure 7: Impulse Responses in the Five-variable System with Consumer Confidence in Place of Stock Price

No Zero Restriction on TFP: Identification I

No Zero Restriction on TFP: Identification II

Zero Restriction on TFP: Identification I

Zero Restriction on TFP: Identification II

Max Share Method: h = 80

Notes: This figure has five panels each of which displays impulse responses to a unit identified shock in the five-variable system with consumer confidence (measured by E5Y) in place of stock price. The first four panels show impulse responses estimated by imposing sign restrictions of Identifications I and II, without (the first and second panels) or with (the third and fourth panels) imposing the zero impact restriction on TFP. When implementing Identifications I and II, the positive sign restriction on the impact impulse response of consumer confidence is imposed. The last panel shows impulse responses to a unit future TFP growth shock estimated by using the Max Share method with the finite horizon (h) of 80 quarters. The black line with circles represents the median response and the shaded gray area represents the confidence interval with the 16th and 84th quantiles. For the purpose of comparison, the corresponding median impulse responses in the five-variable system with stock price (the red line with triangles) are also plotted. The sample period is 1960:Q1 to 2012:Q4 because of availability of consumer confidence series.
**Table 1: Three Sets of Sign Restrictions Imposed to Identify Optimism Shocks**

<table>
<thead>
<tr>
<th></th>
<th>Adjusted TFP</th>
<th>Stock Price</th>
<th>Consumption</th>
<th>Real Interest Rate</th>
<th>Hours</th>
<th>Investment</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Identification I</td>
<td>0</td>
<td>+</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Identification II</td>
<td>0</td>
<td>+</td>
<td>+</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Identification III</td>
<td>0</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Notes: This table describes three sets of sign restrictions imposed to identify optimism shocks: 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 the benchmark seven-variable system or the eight-variable systems where an additional variable of interest is added to the benchmark system and its impulse response is unrestricted.*
Table 2: The Share of Forecast Error Variance Attributable to Optimism Shocks or Future TFP Growth Shocks in the Benchmark Seven-variable System

<table>
<thead>
<tr>
<th>Panel A: The Share of Forecast Error Variance Attributable to Optimism Shocks</th>
<th>Identification I</th>
<th>Identification II</th>
<th>Identification III</th>
</tr>
</thead>
<tbody>
<tr>
<td>h = 0</td>
<td>h = 4</td>
<td>h = 8</td>
<td>h = 16</td>
</tr>
<tr>
<td>Adjusted TFP</td>
<td>0.00</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td>Stock Price</td>
<td>1.00</td>
<td>0.87</td>
<td>0.81</td>
</tr>
<tr>
<td>Consumption</td>
<td>0.04</td>
<td>0.18</td>
<td>0.18</td>
</tr>
<tr>
<td>Real Interest Rate</td>
<td>0.00</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>Hours</td>
<td>0.01</td>
<td>0.22</td>
<td>0.25</td>
</tr>
<tr>
<td>Investment</td>
<td>0.01</td>
<td>0.33</td>
<td>0.35</td>
</tr>
<tr>
<td>Output</td>
<td>0.02</td>
<td>0.30</td>
<td>0.32</td>
</tr>
</tbody>
</table>

Panel B: The Share of Forecast Error Variance Attributable to Future TFP Growth Shocks

<table>
<thead>
<tr>
<th>Max Share: h = 80</th>
<th>Barsky and Sims: H = 80</th>
</tr>
</thead>
<tbody>
<tr>
<td>h = 0</td>
<td>h = 4</td>
</tr>
<tr>
<td>Adjusted TFP</td>
<td>0.00</td>
</tr>
<tr>
<td>Stock Price</td>
<td>0.12</td>
</tr>
<tr>
<td>Consumption</td>
<td>0.43</td>
</tr>
<tr>
<td>Real Interest Rate</td>
<td>0.13</td>
</tr>
<tr>
<td>Hours</td>
<td>0.05</td>
</tr>
<tr>
<td>Investment</td>
<td>0.01</td>
</tr>
<tr>
<td>Output</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Notes: In this table, Panel A reports the share of the forecast error variance attributable to optimism shocks identified by imposing each of three sign restrictions that are described in Table I in the benchmark seven-variable system: Identification I (left panel), Identification II (middle panel), and Identification III (right panel). Panel B reports the share of the forecast error variance attributable to future TFP growth shocks identified by the Max Share or Barsky and Sims' method with the finite horizon of 80 quarters. The numbers represent the median shares, and the numbers in brackets are the confidence intervals with the 16th and 84th quantiles. The letter h refers to the forecast horizon in terms of the unit of quarter.
### Table 3: Comparing with Other Studies

<table>
<thead>
<tr>
<th></th>
<th>Type of Identified Shocks</th>
<th>Restrictions on VAR Size</th>
<th>Lags between the Shock and Actual Changes in TFP</th>
</tr>
</thead>
<tbody>
<tr>
<td>The current paper</td>
<td>Optimism and Future TFP Growth Shocks</td>
<td>No</td>
<td>8-10 Quarters</td>
</tr>
<tr>
<td>Beaudry and Portier (2006)</td>
<td>Optimism and Long-run TFP Shocks</td>
<td>Yes</td>
<td>8-12 Quarters</td>
</tr>
<tr>
<td>Barsky and Sims (2011)</td>
<td>Future TFP Growth Shocks</td>
<td>No</td>
<td>1 Quarter</td>
</tr>
<tr>
<td>Barsky and Sims (2012)</td>
<td>Optimism/Confidence Shocks</td>
<td>Uncertain</td>
<td>1 Quarter (by assumption)</td>
</tr>
</tbody>
</table>

*Notes: This table compares the current paper with three related studies. See Section 4.3 for more details.*
A.1 Appendix (not for publication): Exploring Links between Optimism and Sectoral TFP

In this appendix, we examine how sectoral components of TFP relate to our identified optimism shocks. To this end, we obtain utilization-adjusted TFP measures (again from John Fernald’s website) for the equipment and consumer durables sector and for the non-equipment producing sector. We refer to the first series as a measure of investment sector TFP and the second series as a measure of consumption sector TFP. Using these measures of sectoral TFP, we find that (i) our identified optimism shocks proceed substantial increases in investment sector TFP, while consumption sector TFP does not increase substantially following an optimism shock, and (ii) shocks that maximize the FEV of predictable change in investment sector TFP resemble very closely optimism shocks, while this is not the case for consumption sector TFP. We have also examined the robustness of our other previous results with respect to breaking down TFP into sectoral series. Our previous findings hold up well when using sectoral TFP.\(^1\)

To be more precise, in this extension of our analysis we consider a six-variable system that includes both utilization-adjusted investment sector TFP and consumption sector TFP plus the remaining four variables in our benchmark five-variable system (i.e., stock prices, consumption, the real interest rate and hours worked). We follow similar identification strategies as in our benchmark five-variable model (described in Table 1) to identify optimism shocks. Figure A.1 displays the impulse responses to a unit identified optimism shock and each panel corresponds to one of the three identification strategies. Note that in this exercise two cases are considered: the zero impact restrictions on both sectoral TFP series are imposed (the line with circles) or not (the line with triangles). In all cases, an optimism shock leads to a substantial increase in investment sector TFP in about 10 quarters following the shock. In contrast, consumption sector TFP does not increase significantly above zero even at long horizons. This finding suggests that optimism shocks appear to lead investment sector TFP more than consumption sector TFP. Responses of other variables are generally similar to those in our benchmark five-variable system as in Figure 7.

In the first two panels of Figure A.2, we compare the optimism shocks identified in the above six-variable system (identification II) with future sectoral TFP growth shocks that are identified with the max share method with a horizon of 80 (\(h = 80\)). In the first panel, we apply the max share method to isolate shocks that maximize the share of the FEV of investment sector TFP at eighty quarters. Two cases are considered in the max share method. In one case, the zero impact restriction is imposed on investment sector TFP only and in the other case, the restriction is imposed on both sectoral TFP. The identified impulse responses indicate that the future investment sector TFP growth shock is highly correlated with the optimism shock. In the second panel, we apply the max share method to isolate shocks that maximize the FEV of consumption sector TFP at eighty quarters. We also consider two cases for the zero impact restriction. In one case, the zero impact restriction is imposed on consumption sector TFP only and in the other case, the restriction is

\(^1\)Results are available upon request.
imposed on both sectoral TFP. The impulse responses following a future consumption sector TFP growth shock generally deviate substantially from impulse responses following an optimism shock, indicating the correlation between these two shocks is low.

In the last panel of Figure A.2, we identify a shock that maximizes the FEV of hours at business cycle frequencies (horizons from 6 to 32 quarters) in the six-variable system with sectoral TFP. In one case, we impose the zero impact restriction on both sectoral TFP and in the other case, no zero impact restriction is imposed. The identified impulse responses indicate that such shock is highly correlated with the optimism shock with impulse responses to these two shocks tracing each other closely. This finding suggests that our finding that the optimism shocks are important in driving US business cycle fluctuations is robust when using sectoral TFP series.
Figure A.1: Impulse Responses to an Optimism Shock in the Six-variable System with Sectoral TFP

Identification I

Identification II

Identification III

Notes: This figure has three panels each of which displays impulse responses to a unit optimism shock identified by imposing each of three sign restrictions that are described in Table 1 in the six-variable system with two sectoral TFP: Identification I (left panel), Identification II (middle panel), and Identification III (right panel). The impulse responses of both sectoral TFP are restricted to be zero on impact. The green line with circles represents the median response and the shaded gray area represents the confidence interval with the 16th and 84th quantiles. For the purpose of comparison, the median impulse responses to a unit optimism shock (the red line with triangles), which is identified by imposing the same sign restrictions, but not by imposing zero impact restrictions on both sectoral TFP, are also plotted.
This figure has three panels each of which displays the median impulse responses to a unit shock identified by applying the Max Share method to each of investment-sector TFP at the finite horizon $h = 80$ (the left panel), consumption-sector TFP at $h = 80$ (the middle panel), and hours at the horizons from 6 to 32 quarters (the right panel) in the six-variable with sectoral TFP. When applying the Max Share method to each sectoral TFP or hours, two cases are considered: (1) imposing zero restrictions on the impact responses of both sectoral TFP (the line with triangles) and (2) imposing zero restriction on the impact response of each own sectoral TFP or in the case of hours no zero restrictions on both sectoral TFP (the line with squares). For the purpose of comparison, each panel provides the median impulse responses (the line with circles) and confidence intervals (the shaded area) to a unit optimism shock identified by imposing sign restriction of Identification II (that is, imposing the positive sign restrictions on the impact responses of stock price and consumption, along with zero restrictions on the impact responses of both sectoral TFP).