Mood Swings and Business Cycles: Evidence from Sign Restrictions*

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Abstract

This paper provides new evidence in support of the idea that bouts of optimism and pessimism are an important source of US business cycles. We isolate innovations in optimism or pessimism by using sign-restriction based identification schemes and we document the extent to which such episodes explain macroeconomic fluctuations. Our results suggest that agents' feelings of optimism and pessimism play an important role in US business cycles, accounting for about 30% of business cycle fluctuations in hours and output. Our identified optimism shocks are at least partially rational as total factor productivity (TFP) is observed to rise 8-10 quarters after an initial bout of optimism. While this later finding is consistent with some previous findings in the news shock literature, we cannot rule out that such episodes reflect self-fulfilling beliefs. Our empirical findings are also consistent with the business-cycle features of US labor market variables such as unemployment, the job finding rate and job vacancies, providing further support to optimism shocks being an important source of US business cycles.

JEL Classification: E1, E3
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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. 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.[1] Closely related to this view, because of its shared rational basis, is the news view of mood swings. 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.[2] Finally, there is a third view suggesting that macroeconomic mood swings are only driven by psychological factors and therefore are not directly related to future developments of fundamentals.[3]

The aim of this paper is to contribute to the above debate regarding the source and nature of business cycles.[4] We provide new evidence on the relevance of optimism and pessimism as an important driver of macroeconomic fluctuations by taking the sign-restriction approach to isolate innovations in optimism in structural vector autoregression (SVAR) models. Sign restrictions have been proposed, and used quite extensively in the recent SVAR literature.[5] They serve as an alternative to conventional "zero restrictions" to identify struc-

[1]For example, see Benhabib and Farmer (1994), Benhabib, Wang and Wen (2015), Farmer and Guo (1994), and Gunn and Johri (2013), among others.

[2]For example, see Cochrane (1994a and 1994b), Beaudry and Portier (2004 and 2006), Jaimovich and Rebelo (2009), and Schmitt-Grohe and Uribe (2012). Along this line, Arezki, Ramey and Sheng (2015) recently study the effects of news shocks on current account and other macro variables using giant oil field discoveries as news to future output increases.

[3]For example, see the book by Akerlof and Shiller (2009).

[4]Although 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.

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

tural 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-restriction approach more attractive and credible. In this paper, we implement the theory and numerical algorithms for Bayesian inference of sign restrictions that are recently developed by Arias, Rubio-Ramírez, and Waggoner (2016).[6]

Our identification strategy will employ sign and zero restrictions to identify what we refer to as optimism shocks. The idea is to isolate a shock that induces broad economic booms which are driven by neither improvements in current technology nor expansionary monetary policy. Accordingly, we impose four restrictions in our VAR models. These restrictions define an optimism shock as a shock that is associated with increases in stock prices and consumption and at the same time, the shock is not associated with a decrease in interest rates nor any current movement in measured TFP. We do robustness checks on our results in many dimensions. For example, we consider cases where the VAR model includes 5 to 7 variables, and 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 increases in stock prices and consumption that are orthogonal to current TFP.

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 about 30% of the forecast error variances of hours and output at business-cycle frequencies. So our empirical findings suggest that bouts of opti-

(2011).

[6] Arias et al. (2016) is a substantially revised version of their previous 2014 version. Their theory and algorithms for inference correct problems in the penalty function approach of Mountford and Uhlig (2009), which is a commonly used algorithm for applying sign and zero restrictions.

mism and pessimism are, as the business press would suggest, a very important component in US business-cycle fluctuations.

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 30% of its forecast error variance at business-cycle frequencies—than those in hours per worker (intensive margin)—around 15% 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 identified 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.

We only impose sign and zero restrictions in the short run (indeed, on impact) when we identify the optimism shock. It allows the data to determine if our identified 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, which 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.

In total, our results overwhelmingly suggest that mood swings are very important in business-cycle fluctuations and they are likely to have some grounding in rationality as they appear to be 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 empirical methodology used in this paper cannot separate these two. Moreover, the results do not tell us if the sizes of the initial macroeconomic responses are 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.

In most dimensions, business-cycle fluctuations associated with our identified bouts of optimism have quite intuitive properties and generally conform to the conventional narratives of a expectation-driven boom and the predictions of models for news shocks. 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 the real wage, and a mild increase in the real interest rate—these findings rule out the possibility of our identified optimism shock being a positive labor supply shock or an expansionary monetary shock.

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 in Barsky and Sims (2011 and 2012). However, we argue that our results paint a very different picture of business cycles, the 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 highlight the sources and potential explanations of these differences later in the paper. Our paper is also closely related to Levchenko and Pandalai-Nayar (2015), which identifies a non-technology business-cycle shock from a GDP forecast or a consumer confidence index. Their identified shocks account for a large share of US business-cycle movements and also significantly affect Canadian macro aggregates. We will discuss the relationship between these studies and ours in Section 4.

The remainder of the paper is arranged as follows. Section 2 describes our sign-restriction strategy to identify optimism shocks and the data used in our study. We present the results of our identified optimism shocks in Section 3 and then discuss the related literature in Section 4. Section 5 concludes and discusses directions for future research.

2 Sign Restrictions, Data, and Identification Strategy

In this section, we begin by briefly introducing the sign-restriction approach in the framework of Arias, Rubio-Ramírez, and Waggoner (2016), which recently develops the theory and simulation techniques for the inference of the sign-restriction approach. Then we describe the data and the set of sign and zero restrictions used to identify optimism shocks.

2.1 Sign Restriction Approach

The sign-restriction approach has been widely used in the recent structural vector autoregressions (SVARs) literature. The basic idea of this approach is to impose sign and/or zero 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-restriction approach identifies monetary shocks by imposing such restrictions on the impulse responses of those variables in the data. That is, this identification scheme recovers structural shocks that have a set of pre-specified qualitative features.

To discuss identification of the SVAR with sign and zero restrictions on the impulse response functions (IRFs), let us consider a general form of the SVAR with a lag length p and sample size T, as in Arias et al. (2016):

$$y_t' A_0 = x_t' \mathbb{A}_+ + \epsilon_t' \quad \text{for } 1 \leq t \leq T, \tag{1}$$

where y_t is an $n \times 1$ vector of endogenous variables, $x_t = \begin{bmatrix} y_{t-1}' & \cdots & y_{t-p}' & 1 \end{bmatrix}'$ is an $m \times 1$ matrix with $m = np + 1$, and ϵ_t is an $n \times 1$ vector of exogenous structural shocks—conditional on past information and the initial condition, $(y_0, y_{-1}, \cdots, y_{1-p})$, ϵ_t is Gaussian with $E[\epsilon_t] = 0$ and $E[\epsilon_t \epsilon_t'] = I_n$. A_0 and $\mathbb{A}_+$ are the coefficient matrices:

$$A_0 : n \times n \; ; \quad \mathbb{A}_+ = \begin{bmatrix} A_1' & \cdots & A_p' & c' \end{bmatrix}' : m \times n. \tag{2}$$

where A_l is an $n \times n$ matrix of structural parameters for $0 \leq l \leq p$ with A_0 invertible and c is a $1 \times n$ vector of structural parameters for a constant term—in Arias et al. (2016), $(A_0, \mathbb{A}_+)$ is referred to as the structural parameterization.

To identify the j^{th} structural shock in ϵ_t (e.g., the optimism shocks in our study), we impose both sign and zero restrictions on the IRFs to the shock, which are functions of the structural parameters, $(A_0, \mathbb{A}_+)$. The impulse response matrix at horizon h, which is denoted by $L_h(A_0, \mathbb{A}_+)$, is calculated recursively as follows:

$$L_h\left(A_0,\mathbb{A}_+\right)=\begin{cases}\left(A_0^{-1}\right)' & \text{for } h=0\\ \\ \sum\limits_{l=1}^{h}\left(A_l A_0^{-1}\right)' L_{h-l}\left(A_0,\mathbb{A}_+\right) & \text{for } 1\leq h\leq p\\ \\ \sum\limits_{l=1}^{p}\left(A_l A_0^{-1}\right)' L_{h-l}\left(A_0,\mathbb{A}_+\right) & \text{for } p<h<\infty\end{cases},$$

where the j^{th} column of $L_h\left(A_0,\mathbb{A}_+\right)$ is the impulse response vector to the j^{th} structural shock in ϵ_t at horizon h and thus the element in row i and column j of $L_h\left(A_0,\mathbb{A}_+\right)$ is the impulse response function of the i^{th} variable in y_t to the j^{th} structural shock at horizon h. Let us denote an $nr\times n$ matrix that stacks the impulse response matrices at all relevant horizons by:

$$F\left(A_0,\mathbb{A}_+\right): nr\times n \tag{3}$$

where $nr=n\times r$ with r being the number of relevant horizons. Let S_j and Z_j define the sign and zero restrictions on the j^{th} structural shock for $1\leq j\leq n$, where S_j is a $s_j\times nr$ matrix of full row rank with $s_j\geq 0$ and Z_j is a $z_j\times nr$ matrix of full row rank with $0\leq z_j\leq n-j$. Then, the sign and zero restrictions imposed to identify the j^{th} structural shock are expressed as follows:

$$S_j F\left(A_0,\mathbb{A}_+\right)\mathbf{e}_j>0 \quad \text{and} \quad Z_j F\left(A_0,\mathbb{A}_+\right)\mathbf{e}_j=0 \quad \text{for } 1\leq j\leq n \tag{4}$$

where $\mathbf{e}_j$ is the j^{th} column of I_n.

Arias et al. (2016) develop the theory on conditionally agnostic priors and posteriors subject to sign and zero restrictions and propose numerical algorithms for Bayesian inference when using sign and/or zero restrictions to identify SVARs.[7] To identify optimism shocks with both sign and zero restrictions and make inference in our empirical studies, we implement the numerical algorithm (Algorithm 4) proposed by Arias et al., which makes independent draws from the conditionally agnostic posterior over the structural parameterization $(A_0, \mathbb{A}_+)$ subject to the sign and zero restrictions.[8] This algorithm ensures that identification solely comes from the intended sign and zero restrictions. We skip the details of their algorithm to save space and refer to Arias et al. (2016) for more information.

2.2 Data and Identification Strategy

In our empirical studies, we use quarterly US data of the sample period from 1955:Q1 to 2012:Q4.[9] Our dataset contains the following variables: TFP, stock price, consumption, investment, output, (total) hours worked, the real interest rate, the inflation rate, the real wage, real inventories, and consumer confidence. To further investigate the role of optimism shocks in the labor market, we also consider the following labor-market variables: the unemployment rate, hours per worker, the labor force participation rate, the job finding rate, the job separation rate, job vacancies, and the vacancy-unemployment ratio.

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.[10] We also report

[7]The sign-restriction approach relies on Bayesian inference, and as pointed by Arias et al. (2016), priors play a crucial role in the sense that if the prior conditional on the sign and zero restrictions is not conditionally agnostic, the prior affects identification and therefore identification does not only come from the stated sign and zero restrictions. This problem exists in the penalty function approach of Mountford and Uhlig (2009), a commonly used algorithm for the sign-restriction approach.

[8]Arias et al. (2016) show that when zero restrictions are imposed, a conditionally agnostic prior and posterior are defined over a chosen parameterization subject to the zero restrictions and the details of their proposed numerical algorithm depend on such a choice. All results reported in this paper are from the structural parameterization, but are also robust to an alternative parameterization, the impulse response function parameterization. The results based on the impulse response function parameterization will be discussed in Section 3.4.

[9]The results reported in this paper are robust to the sample period from 1955:Q1 to 2007:Q4, which excludes the recent global financial crisis.

[10]Our (adjusted and non-adjusted) TFP series are obtained from John Fernald's website. We also use adjusted TFP in Beaudry and Lucke (2010) as a robustness check. Our main findings reported through this paper hold up well with this alternative measure of adjusted TFP.

some results using a non-factor-utilization-adjusted TFP series to illustrate the difference—this series is also taken from John Fernald's website. In general, we believe that the adjusted TFP series is a much better measure of true technological progress and we therefore take it as our baseline series for TFP.[11]

Our stock price measure is the end-of-period Standard and Poor's 500 composite index (obtained from the *Wall Street Journal*) divided by the CPI—CPI of all items for all urban consumers, which is obtained 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. (Total) 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 CPI. Our measure of inventories is real non-farm private inventories from the BLS, which is then divided by the population series to convert it into a per capita term.

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 contin-

[11] Jaimovich and Rebelo (2009) and Nam and Wang (2010) 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.

uous 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.[12]

For the labor market variables, the labor force participation rate and the unemployment rate are obtained from the BLS. 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 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), and the vacancy-unemployment ratio is constructed using this measure of job vacancies and unemployment series.[13]

In our benchmark VAR model, y_t contains five variables ($n = 5$): (adjusted) TFP, stock price, consumption, the real interest rate, and (total) hours worked. All variables are logged except for the real interest rate and enter the system in levels.[14] A constant and four lags ($p = 4$) are also included in our benchmark system. Our results are robust to different numbers of lags. When we consider other variables, we mainly replace the last variable in the benchmark five-variable system (hours worked) with one of the other variables such as investment and output. We also consider larger VAR systems by adding other variables, say, the real wage, to the benchmark five-variable system.

To identify optimism shocks, we impose a set of the sign and zero restrictions on the impact impulse responses of TFP, stock price, consumption, and the real interest rate, while leaving impulse responses of all other variables in the model unrestricted. This set of restrictions is summarized in Table 1. In our identification strategy, we impose the zero impact re-

[12]The Survey of Consumers data starts in 1960:Q1 and the Conference Board data starts in 1967:Q1.

[13]We thank Regis Barnichon for providing the updated HWI data.

[14]As stressed by Hamilton (1994), estimation of a VAR model in levels is robust to cointegration of unknown form and produces consistent estimates of the impulse response functions.

striction on TFP such that the identified optimism shock is orthogonal on impact to changes in TFP, which differentiates our optimism shocks from current technology improvements. This zero restriction has also been used in the news TFP shock literature (e.g., 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 TFP shocks. In addition, we impose positive sign restrictions on the impact impulse responses of stock price and consumption. 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. For example, Beaudry and Portier (2006) take the view that stock price is likely a good indicator for capturing any changes in agents' expectations about future economic conditions. Cochrane (1994b) argues that agents may have advance information about future economic conditions that they use when making consumption decisions. The restrictions on TFP, stock price, and consumption might still be viewed as insufficient to isolate optimism shocks, as monetary shocks may also satisfy these zero and sign restrictions. In many models, an expansionary monetary shock could induce rises in stock price and consumption, but no immediate effect on TFP. For this reason, we require that the impulse response of the real interest rate be non-negative on impact following an optimism shock.[15]

In all alternative VAR systems that are larger than the benchmark five-variable system, we still use the same set of zero and sign restrictions as described above, thereby leaving the impulse responses of newly added variables unrestricted.

3 Results

This section presents our main findings in the benchmark system, the results for labor-market variables and other variables of interest, and the results in subsamples and various

[15]Moreover, there could be other structural shocks that satisfy the set of the zero and sign restrictions we impose to identify optimism shocks. For instance, a positive labor supply shock could be such a shock. We will therefore do robustness checks on whether we indeed identify optimism shocks.

robustness checks.

3.1 Results in the Benchmark System

Figure 1 displays the impulse responses to an optimism shock identified in our benchmark five-variable system that includes TFP, stock price, consumption, the real interest rate and hours worked. In the figure, the left panel is the case that TFP is measured by the factor-utilization adjusted TFP series and the right panel is the case that TFP is measured by the non-adjusted TFP series. In each panel, we also report the impulse responses of investment and output, which are estimated from two alternative five-variable systems in which hours worked is replaced by investment and output, respectively.[16]

In all five-variable systems, the following restrictions are imposed to identify optimism shocks: TFP is restricted to be zero on impact of the shock, and stock price and consumption are restricted to be positive on impact of the shock. As discussed earlier, these restrictions capture the standard narratives of optimism-driven economic booms that are not associated with current improvements in technology. In addition, the real interest rate is restricted to be positive on impact of the shock, which distinguishes our optimism shock from an expansionary monetary shock. Hours, investment and output are left unrestricted in these exercises.

We first focus on the results when adjusted TFP is used, which is reported in the left panel of Figure 1. The results are consistent with an expectation-driven economic boom as reported in Beaudry and Portier (2006). Stock price, consumption and the real interest rate all rise on impact, while TFP does not change on impact. This is by construction as they are the identifying restrictions. Following the shock, consumption continues to increase significantly and then settles at its new long-run level, indicating an expansion of the real

[16]The impulse responses of other four variables in these two alternative systems are virtually identical to those in the benchmark system with hours worked. So they are only reported in the online appendix to save space.

economy. Hours worked barely changes on impact, but increases gradually over time. It exhibits a hump-shaped response before converging back to the initial level. Investment and output display a similar hump-shaped pattern as hours, but converge to their new long-run levels. These impulse responses indicate that the economic boom following the identified optimism shock is a broad one, in which all major aggregate macroeconomic indicators expand persistently.

There are two important aspects of TFP to notice in this panel. First, the median response of TFP does not rise above zero until about ten quarters following the identified optimism shock, even though consumption, hours, investment and output all increase strongly and reach their peaks before TFP starts to rise at the tenth quarter. Since the initial increases in consumption, hours, investment and output following the identified shock are not associated with an actual increase in TFP, it suggests that the economic boom is driven by optimism rather than an actual increase in TFP.

Second, TFP eventually rises to a higher long-run level, though no such restriction is imposed ex ante. It suggests that the initial increase in optimism either anticipates the eventual rise in TFP (the news view of mood swings) or causes it (the self-fulfilling feedback loop view), indicating 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 and consumption that are orthogonal to TFP induce a generalized boom of the economy, which precedes an eventual rise in TFP.

The right panel of Figure 1 presents the impulse responses estimated using the non-adjusted TFP series as a measure of TFP. Overall, the impulse responses are similar to those reported in the left panel. But, there is one exception. 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 starts to rise to a permanently higher long-run level. The period between the arrival of optimism and the starting of an eventual rise in TFP is about ten quarters no matter if we use adjusted or non-adjusted TFP as a measure of TFP. Our results show that the sign-restriction approach 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.

Table 2 reports the share of the forecast error variance (FEV) that is attributable to optimism shocks for each variable. Consistent with the results of the impulse responses reported in Figure 1, optimism shocks are found to play an important role in explaining aggregate macroeconomic fluctuations at business-cycle frequencies. In Panel A of Table 2 for the case in which adjusted TFP is used, optimism shocks account for around 30% of the FEV of hours and about 40% of the FEVs of consumption, investment and output at horizons from 8 to 32 quarters. Around 20% of the FEV of adjusted TFP at the horizon of 40 quarters is explained by optimism shocks. The FEV decomposition estimated using non-adjusted TFP is qualitatively similar (Panel B). There are only two noticeable differences. First, 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. Second, the optimism shocks identified using non-adjusted TFP account for less the FEVs of consumption, hours, investment and output than the optimism shocks identified using adjusted TFP. These results highlight the importance of adjusting for utilization in identifying optimism (or news TFP) shocks correctly.

3.2 Results of Labor-market Variables

By exploring key labor-market variables, we now show that our identified optimism shocks are consistent with business-cycle properties of US labor market. It corroborates the findings in the previous section and provides further support that optimism shocks play an important role in driving US business cycles.

Besides (total) hours worked, several other labor market variables are found in previous empirical studies to have specific business-cycle features and these features have been used to test the empirical relevance of various labor-market models. For instance, Shimer (2005) documents that standard search and matching model cannot generate the observed business-cycle fluctuations of unemployment and job vacancies. Empirically, a structural shock should not only account for a large share of business-cycle fluctuations in total hours worked, but also be able to match the documented empirical features of other labor-market variables, if it is truly a driving force behind US business cycles. For instance, US business-cycle fluctuations of total hours worked are mainly due to changes in unemployment rather than changes in hours per worker, as documented in previous empirical studies (e.g., Cho and Cooley, 1994). If a shock cannot match this feature in the data, it may not reveal the true mechanism of US business-cycle fluctuations even if it happens to match business-cycle features of total hours worked. In that case, it casts doubts on the shock being a major driving force for US business cycles.

In this subsection, we investigate the effects of our identified optimism shock on a group of labor market variables and the results are compared with previous empirical findings on the business-cycle properties of these labor market variables. In these exercises, total hours in the benchmark five-variable model is replaced by each of the following labor-market 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.[17] In these five-variable systems with one of the above labor-market variables, optimism shocks are identified by imposing the same zero and sign restrictions on TFP, stock price, consumption and the real interest rate as before. In all cases, the labor-market variables remain unrestricted—that is, we remain agnostic about the effects of optimism shocks on these variables.[18] Figure 2 presents our results for the labor-market variables. We only report the impulse responses of the labor-market variables because the responses of other four variables are virtually identical to those reported in the left panel of Figure 1.

Several interesting findings stand out in Figure 2. In the left panel, the median response of hours per worker rises immediately following the optimism shock, but the increase is much temporary and smaller than that of total hours following an optimism shock—the identified optimism shocks account for around 15% of the forecast error variance (FEV) of hours per worker at business-cycle frequencies (see Table 3). It indicates that the intensive margin (hours per worker) explains only a limited fraction of fluctuations in total hours 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 per worker in the US, while the remainder is through changes in employment.[19] On the other hand, the identified optimism shock substantial affects the unemployment rate, whose impulse response mirrors the response of total hours—the identified optimism shocks explain over 30% of the FEV of the unemployment rate at business-cycle frequencies.[20] In addition, the optimism shock is found to have no significant effect on the labor force participation rate: it accounts for only about 10% of the FEV of the labor force participation rate. The responses

[17]From now on, we use adjusted TFP as our measure of TFP.

[18]Moreover, conventional narratives of optimism/news-driven business cycles usually do not specify the effects of optimism shocks on these labor-market variables considered here.

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

[20]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.

of all these four labor market variables suggest that following optimism shocks, changes in US total hours worked are mainly due to changes in employment (extensive margin). This pattern matches the business-cycle properties of US labor markets that are documented in previous empirical studies.

In the right panel of Figure 2, we further investigate if the effect of our identified optimism shocks on the unemployment rate is consistent with empirical findings in the business-cycle literature on the labor market. A decrease in the unemployment following the optimism shock can come from either an increase in the job finding rate or a decrease in the job separation rate. We document that the job finding rate rises strongly following the optimism shock while the job separation rate falls only modestly— the identified optimism shocks are found in Table 3 to account for around 35% and 20% of the FEVs 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 is more important than the job separation rate in accounting for the fluctuations in the US unemployment rate.

Figure 2 shows that the increase in the job finding rate following an optimism shock is mainly due to job creation rather than a decrease in unemployment. Following an optimism shock, the increase in the job finding rate is accompanied with a strong increase in job vacancies. As a result, the ratio of job vacancies to unemployment rises sharply, raising the possibility of finding a job. In Table 3, the optimism shock explains similar shares of the FEVs of the job finding rate (35%), job vacancies (30%) and the ratio of job vacancies to unemployment (35%). These patterns are consistent with previous empirical findings of US labor market.

All the above results suggest that our identified optimism shock not only accounts for a large share of total hours, but also matches the underlying mechanisms of labor-market fluctuations over business cycles. These additional results provide strong supporting evidence that the optimism shock is an important source of US business cycles.

Furthermore, the responses of the unemployment rate, the job finding rate, job vacancies, and the vacancy-unemployment ratio all peak before adjusted TFP starts to increase, suggesting that these documented business-cycle features of US labor market are driven by optimism rather than an actual increase in TFP.

3.3 Results of Subsamples and Other Variables of Interest

We now investigate the effects of optimism shocks on several other variables of interest and also check the robustness of our findings in different subsample periods. The results are presented in Figure 3. The left panel of the figure displays the impulse responses of four variables of interest to an optimism shock: the real wage, the inflation rate, real inventories and a measure of consumer confidence. For each variable, the impulse response is estimated in a six-variable system that is obtained by adding the variable to the benchmark five-variable system. The optimism shocks are identified by using the same zero and sign restrictions as in the benchmark model, leaving the newly added variable unrestricted. The only exception is when we consider the inflation rate, in which case we remove the sign restriction on the real interest rate from the benchmark restrictions. The reason will be discussed when we present the result for the inflation rate.

Since the addition of a new variable does not change any of the findings from the benchmark five-variable system, we only report the impulse responses of the newly added variables in Figure 3. In the first exercise, the real wage is added to the five-variable system. Following an optimism shock, the real wage increases significantly and converges to a permanently higher level. Our results are robust to 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 are obtained from the BLS. 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 five-variable system. In this case, we modify our sign restrictions slightly by removing the positive sign restriction on the real interest rate. The real interest rate is calculated from inflation and we do not want to implicitly restrict the behavior of inflation by imposing a restriction on the real interest rate in this exercise. It is interesting that inflation almost does not change in response to our identified optimism shock, suggesting optimism shocks appear to cause booms with neither TFP nor inflation rising for an extended period of time. Our finding is robust if we exactly follow the benchmark restrictions—in this case, inflation indeed falls even more significantly following an optimism shock.[21] This result is difficult to reconcile with a standard demand-driven new-Keynesian model. Beaudry and Portier (2013) propose a multi-sector model in which business cycles are driven by changes in perceptions about the future and agents are not mobile across sectors. The model can successfully replicate the non-inflationary optimism/expectation-driven economic boom as documented in this paper.

In the left panel of Figure 3, the impulse response of real inventories increases gradually following the identified optimism shock and peaks before TFP rises above zero. It eventually converges to a new long-run level. This finding is consistent with the fact that inventories are usually pro-cyclical in the data, supporting that the identified optimism shock is important in driving US business cycles. However, Crouzet and Oh (2016) show in standard business-cycle models with inventories that a positive news TFP shock induces a decline in inventories. This discrepancy between the predictions of theoretical models and the empirical findings in the data deserves further investigation in the future. Such studies might be able to provide guidance to disentangling news TFP shocks from self-fulfilling sentiment shocks (two interpretations of our identified optimism shocks) and also shed light on the transmission mechanisms of these shocks in standard models and in the data since inventories appear to

[21]The results for inflation are robust to measuring inflation by the growth rate of the GDP implicit deflator. In this case, optimism shocks are found to be associated with a significant fall in inflation.

behave differently under news and sentiment shocks.

While we believe that stock price and consumption are the best indicators of confidence and changes in agents' expectations about future economic conditions, there are surveys that provide alternative measures of consumer confidence or sentiment on future economic conditions. Despite various data issues related to such survey data, we add a survey measure of consumer confidence to our benchmark five-variable system to examine whether our optimism shocks are also reflected in such surveys. The last chart in the left panel of Figure 3 shows the impulse response of consumer confidence to an optimism shock, where consumer confidence is measured by the Survey of Consumers of the University of Michigan (denoted by E5Y).[22] Following an identified optimism shock, the measure of consumer confidence rises strongly on impact and then exhibits a persistent decline over time. In addition, we find that optimism shocks account for a large fraction of the FEV of the confidence measure. This finding is consistent with Barsky and Sims (2011), suggesting that the measures of consumer confidence are closely related to our notion of optimism.

The right panel of Figure 3 shows that our main findings in the full sample hold up well in two important subsamples, the post-1983 subsample and the pre-1978 subsample. The pre-1978 subsample covers the period from 1955:Q1 to 1978:Q4 (the line with squares). The post-1983 subsample covers the period from 1983:Q1 to 2012:Q4 (the line with triangles). The full sample ranges from 1955:Q1 to 2012:Q4 (the line with circles). We exclude the sample period from 1979:Q1 to 1982:Q4 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

[22]Our results are robust to other measures of consumer confidence such as E12M in the University of Michigan survey or the confidence measure from Conference Board, which are described in Section 2.2.

Rebelo (2009).

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 consumption, hours, and investment in the more recent subsample. We also document that optimism shocks account for a larger share of the FEVs of consumption and hours in the post-1983 subsample than in the pre-1978 subsample.[23] These findings suggest that optimism shocks may have become more important in driving US 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.

3.4 Additional Robustness Checks

We conduct robustness checks in many other dimensions and briefly describe some of these results in this section. Detailed results are only reported in the online website.

As mentioned in Footnote 8, the results reported in this paper are based on the structural parameterization subject to the zero restriction over which the conditionally agnostic prior and posterior are defined. We show that our findings are robust to an alternative parameterization based on the impulse response functions, which is referred to as the impulse response function parameterization in Arias et al. (2016). Figure A.1 in the online appendix compares the results based on this alternative (impulse response function) parameterization with the benchmark results in Figure 1 that are based on the structural parameterization. It is clear that our main findings hold up well under this alternative parameterization when implementing the theory and algorithm of Arias et al. (2016).

In another robustness check, we find that our main results are robust to removing the

[23]The results are available upon request.

positive sign restriction on the real interest rate (see Figure A.2 in the online appendix). This robustness check serves two purposes. First, a positive sign restriction on the real interest rate implicitly imposes a negative sign restriction on inflation, which could be the source that our identified optimism shocks are associated with non-inflationary economic booms. The results in this robustness check exclude that possibility. Second, the results here also show that our findings are robust to cases with less sign restrictions. Arias et al. (2016) document that our results are weakened if only two restrictions are imposed: a positive restriction on stock price and a zero restriction on TFP. The robustness check here shows that in addition to the zero restriction on TFP, as long as positive restrictions are imposed on both stock price and consumption, the main findings in this paper hold up qualitatively and quantitatively well. We believe that a positive sign restriction only on stock price or consumption is not sufficient to identify optimism shocks since many other structural shocks could satisfy such restrictions. Therefore, a more reasonable identification scheme should at least include positive sign restrictions on both stock price and consumption.

Standard narratives of optimism-driven business cycles and previous empirical and theoretical studies on the topic indeed suggest that more restrictions should actually be imposed when we identify optimism shocks. For instance, studies on news TFP shocks, which is one form of our optimism shocks, are found to generate strong co-movements in hours, output, and consumption. See Beaudry and Portier (2006) and Jaimovich and Rebolo (2009) for examples of empirical and theoretical studies, respectively. As a result, it is even desirable to simultaneously impose a positive sign restriction on hours in our benchmark model to pick up the effects of optimism shocks. Adding such a restriction indeed strengthens our results with identified optimism shocks accounting for over 40% of the FEV of total hours worked.

The stronger results are not due to mechanically adding more sign restrictions. We impose a negative sign restriction on hours, as Barsky and Sims (2011) document in their study, in a six-variable system that is obtained by adding output to the benchmark five-variable system.

In this exercise, we identify optimism shocks by imposing the negative sign restriction on hours (on impact or for the first four quarters) as well as our benchmark restrictions on TFP, stock price, consumption and the real interest rate. The identified shock only accounts for less than 10% of the FEV of hours worked as in Barsky and Sims (2011). Unlike in Barsky and Sims (2011), TFP does not rise immediately even in the cases that hours and output decrease on impact of the shock—see the middle and right panels in Figure A.3. There is still a delay of about 10 quarters before TFP starts to rise to its new long-run level, with consumption and output reaching their peaks before the tenth quarter.

Our results are also robust in a six-variable system that is obtained by replacing (aggregate) adjusted TFP series in our benchmark five-variable system with two sectoral TFP series—investment- and consumption-sector adjusted TFP.[24] In this robustness check, we examine how sectoral components of (aggregate) TFP relate to our identified optimism shocks. Besides our standard sign restrictions on stock price, consumption, and the real interest rate, we consider three cases for the zero restriction on TFP: the zero impact restriction is imposed on both investment-sector TFP and consumption-sector TFP in the first case, and in the remaining two cases, it is only imposed on either investment-sector TFP or consumption-sector TFP. The results are reported in Figure A.4. We find that (i) investment-sector TFP rises substantially (about 1%) in the long run following our identified optimism shocks, while the increase in consumption-sector TFP is much smaller (about 0.1%) and statistically insignificant; (ii) Both consumption and hours worked increase strongly and reach their peaks before investment-sectoral TFP rise significantly above zero, indicating an optimism-driven economic boom that is unrelated to actual increases in investment-sector TFP.

Finally, we identify optimism shocks in a seven-variable system that includes hours, investment, and output together as well as adjusted TFP, stock price, consumption and

[24] We obtain factor-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.

the real interest rate. Our findings in Section 3.1 are robust to this large system, though including more variables reduces statistical precisions. The results are reported in Figure A.5.

4 Discussion of the Related Literature

According to the findings in Section 3, the identified optimism shocks in this paper can either reflect news about future TFP or capture self-fulfilling sentiment shocks that cause subsequent increases in TFP. Several previous studies on news or sentiment shocks are closely related to this paper. In this section, we connect the results in our paper to those in the related previous studies. In particular, we compare this paper with Barsky and Sims (2011 and 2012), Beaudry and Portier (2006) and Levchenko and Pandalai-Nayar (2015).

Table 4 summaries some differences among our paper and the related studies. First, the shocks that are identified in these studies are different, though all of them are labeled as news or confidence/optimism shocks. Beaudry and Portier (2006) identify a news shock reflected in stock prices. They interpret the identified shock as news about future TFP because the shock is found to be closely linked to long-run TFP movements. Our study identifies an optimism shock that could reflect news about future TFP as in Beaudry and Portier (2006). However, our identified shocks may also capture bouts of optimism/pessimism that cause subsequent changes in TFP. The sign-restriction approach implemented in this paper can also be applied to much larger VAR systems than those in Beaudry and Portier (2006).[25] 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 investigate the optimism shocks in driving well-documented labor-market properties during business cycles.

[25] When applied to large VAR systems, Beaudry and Portier's (2006) identification scheme has to impose short-run zero restrictions that may be difficult to justify. In particular, Kurmann and Mertens (2014) show that Beaudry and Portier's (2006) identification scheme does not have a unique solution when applying to vector error correction models (VECMs) with more than two variables due to a particular interplay of cointegration assumptions and long-run restrictions.

Barsky and Sims (2011) propose a new scheme to identify a shock which has no immediate impact on TFP but becomes a dominant force of driving subsequent changes in TFP.[26] Unlike our findings, the identified shock in Barsky and Sims (2011) precedes eventual TFP growth by only one quarter and appears to cause falls in hours, investment and output on impact of the shock. Our results in this paper suggest that economic expansions (especially in the recent data after 1985) 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 an immediate rise in productivity as Barsky and Sims (2011) argue.[27]

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 discuss 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

[26]Nam and Wang (2015) examine the international transmission of news shocks to TFP using Barsky and Sims' (2011) identification scheme.

[27]When implementing Barsky and Sims' (2011) identification scheme, TFP measure that is adjusted for factor utilization is essential. As found in Section 3.1, our sign restriction strategy to identify optimism shocks—it could be news shocks—is robust to non-adjusted TFP.

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 falls in investment and hours. 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.[28] For example, their findings indicate that an increase in confidence of itself does not lead to increased economic activity. According to them, the eventual increase in economic activity following an increase in consumer confidence only arises once TFP starts growing. They therefore conclude that the expansion which follows a news/confidence shock is actually driven by the contemporaneous rise in TFP as in the RBC literature, not by the change in expectations.[29] 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

[28]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.

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

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.

Therefore, the issue boils down to if there is a delayed increase in TFP in the data following news/optimism shocks and if the economy expands before the actual increase in TFP. From the large set of results we present in this paper, we believe that the patterns that support expectation/optimism-driven business cycles are robust and should be seen as reliable. In addition, under certain subsamples and specifications, the results from Barsky and Sims' (2011) identification strategy are also favorable to theories of news-driven business cycles. Sims (2016) documents that in some specifications the results from using the most recent vintage (year 2015) of the adjusted TFP data are consistent with the results reported in this paper, which exhibits a delayed increase in TFP and substantial increases in hours, consumption and output before the actual increase in TFP.[30] Moreover, using Barsky and Sims' identification strategy, we find a lagged increase in TFP and an increase in hours (rather than a decrease as in Barsky and Sims, 2011) following a positive news TFP shock for the post-1984 subsample in the four-variable system in Barsky and Sims (2011). The results are also more pronounced when we use a larger truncation horizon than the one used in Barsky and Sims (2011) to minimize the effect of noises to short-run TFP movements.[31]

Our paper is also related to Levchenko and Pandalai-Nayar (2015), which identifies a non-technology business cycle shock (labeled as "sentiment" shock). Under their identification strategy, the sentiment shock is orthogonal to both surprise-TFP and news-TFP shocks that are identified from Barsky and Sims' (2011) identification scheme. In addition, the identified sentiment shock explains as much as possible the short-run residual forecast error variance

[30]Kurmann and Otrok (2016) find that using the most recent vintage of the adjusted TFP data does not affect the main results in Kurmann and Otrok (2013).

[31]The results are available upon request.

of a market sentiment measure (e.g., surveys of GDP forecast or consumer confidence). A positive sentiment shock induces a broad economic boom with increases in consumption, output and hours. The identified sentiment shock also accounts for a large share of business-cycle fluctuations of US aggregate variables. For instance, it explains over 50% of the forecast error variance of hours at horizons of 2 years and less.

Although the sentiment shock in Levchenko and Pandalai-Nayar (2015) and our identified optimism shock display some similar patterns in generating a broad economic boom, there are important differences between these two shocks. On the one hand, Levchenko and Pandalai-Nayar's (2015) identification strategy may be less restrictive than ours. Their sentiment shock may include all structural shocks that are orthogonal to TFP and drive short-run movements of an expectational variable as they identify the shock by maximizing its contributions to the short-run (the first two quarters) forecast error variance of the expectational variable. We only impose impact restrictions and do not require our shock to account for all short-run changes in expectational variables. This may explains that the sentiment shock in Levchenko and Pandalai-Nayar (2015) appears to account for more forecast error variances of the expectational variable than our optimism shock. Some of the structural shocks captured in Levchenko and Pandalai-Nayar's (2015) sentiment shock may simultaneously influence the expectational variable and the aggregate variables such as consumption and hours worked in the short run. As a result, their sentiment shock usually also explains more short-run fluctuations of aggregate macroeconomic variables than our optimism shock.

On the other hand, Levchenko and Pandalai-Nayar's (2015) identification strategy is more restrictive than ours. Their sentiment shock is restricted not to be related to any TFP changes: either surprise TFP changes (surprise-TFP shock) or predicted changes in future TFP (news-TFP shock). In contrast, we do not impose restrictions on whether optimism shocks affect future TFP or not, though the optimism shocks are restricted to have no immediate impact on TFP. Indeed, we document an increase in future TFP following an initial bout of optimism, indicating that our optimism shocks have some grounding in rationality.

In summary, the sentiment shock in Levchenko and Pandalai-Nayar (2015) and our optimism shocks are two different types of shocks, though they display some similar business-cycle properties. Their shock captures all short-run movements of an expectational variable but are not related to any TFP movements. Our shock is only restricted to induce a general economic boom on impact and is found to lead future TFP increases.

Neither is our optimism shock likely a combination of the sentiment shock and the new-TFP shock that are identified in Levchenko and Pandalai-Nayar. Hours worked falls following an increase in the identified news-TFP shock in Levchenko and Pandalai-Nayar (see Figure 2 in their paper). It is the opposite in our results. In addition, our results are robust to imposing a positive restriction on hours in one of exercises of Section 3.4, which separates our findings from Levchenko and Pandalai-Nayar's.

5 Conclusion

Many economic commentators view sentiments of optimism and pessimism as important drivers of business cycle fluctuations. In this paper, we explore this issue by 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 an important driving force of business cycles. We find that our identified optimism shocks lead to gradual and substantial pick-ups in investment, output, hours worked (or other labor market variables 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.

The second question we ask in the paper is whether our identified optimism shocks should be interpreted as mainly reflecting psychological phenomena or should they be seen as potentially grounded in rationality. We document that our identified optimism shocks have some grounding in rationality. These shocks are followed after 2 to 3 years by an increase in measured TFP, though we do not impose such restrictions ex ante. 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.

Our results differ quite substantially from those reported in Barsky and Sims (2011 and 2012) and Levchenko and Pandalai-Nayar (2015), which pursue a similar issue using different methodologies. We discuss the sources of differences in the results and provide some reconciliation to better understand the literature. Providing a structural model capable of quantitatively replicating the news/expectation-driven business cycles that we documented in this paper is in our view an important challenge to model builders. As this question is beyond the scope of the paper, we leave it for future work.

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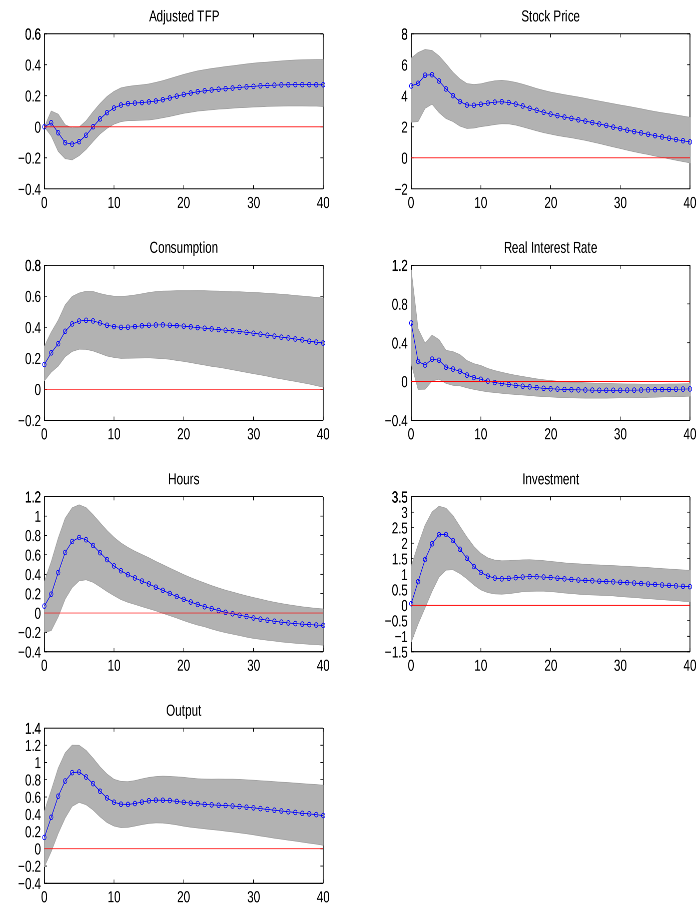
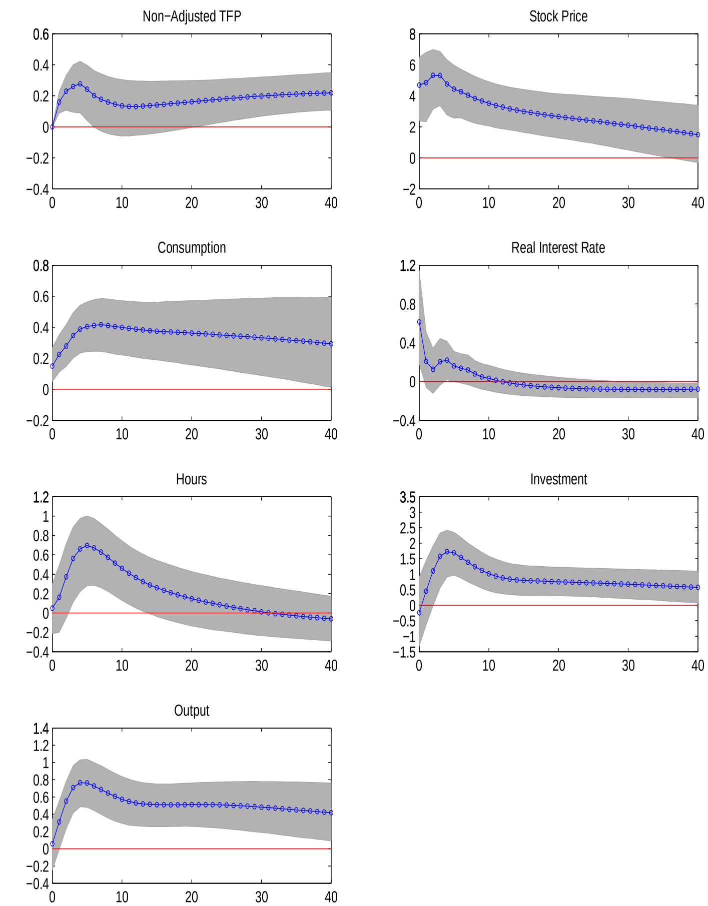
Figure 1: Impulse Responses to an Optimism Shock when TFP is Measured by Adjusted or Non-Adjusted TFP Series

Adjusted TFP

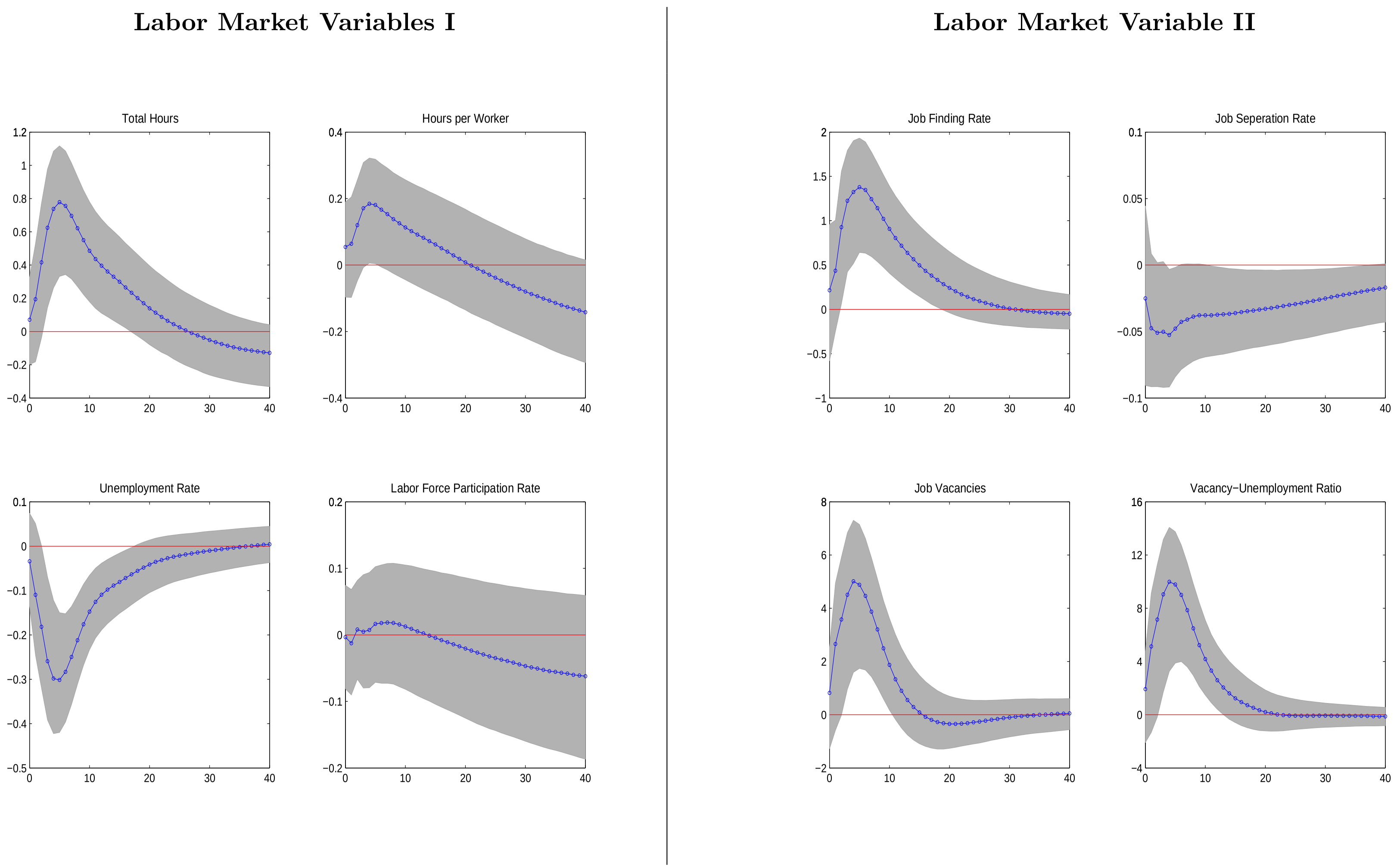


Non-Adjusted TFP



Note: This figure displays the impulse responses to the identified optimism shock in the benchmark five-variable system. TFP is measured by the adjusted (non-adjusted) TFP series in the left (right) panel. In both panels, the impulse response of Investment (Output) is estimated from a five-variable system in which Hours in the benchmark five-variable system is replaced by Investment (Output). The blue line with circles is the median response and the shaded gray area represents the confidence interval with the 16th and 84th quantiles. The vertical axis displays the percentage deviation from the state without the shock and the unit of the horizontal axis is quarter.

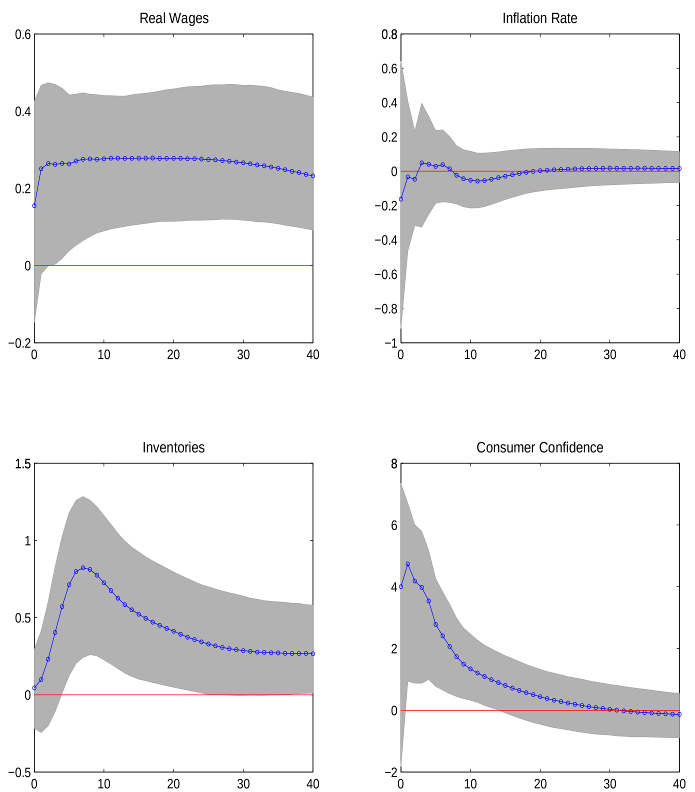
Figure 2: Impulse Responses of Labor Market Variables to an Optimism Shock



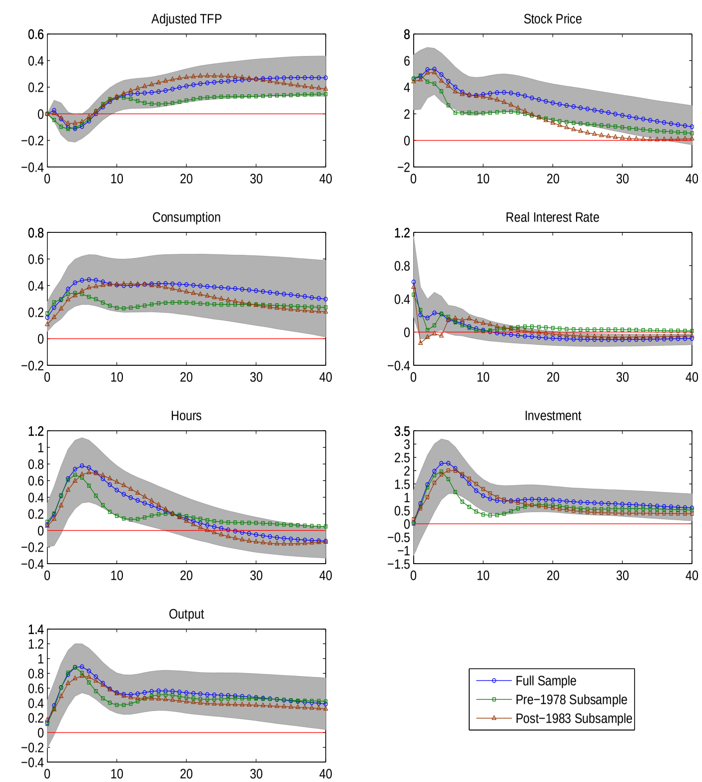
Note: This figure displays the impulse responses of eight labor market variables to the identified optimism shock in the benchmark five-variable system, (Adjusted TFP, Stock Price, Consumption, Real Interest Rate, Each Labor Market Variable). The blue line with circles represents the median response 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.

Figure 3: Impulse Responses to an Optimism Shock: Other Variables of Interest and Two Subsample Periods

Other Variables of Interest



Subsample Periods



Note: This figure has two panels. The left panel displays the impulse responses of four variables of interest to the identified optimism shock. Each of these four impulse responses is estimated in the six-variable system that is obtained by adding each variable to the benchmark five-variable system, (adjusted-TFP, stock price, consumption, the real interest rate, hours). The right panel displays the estimated median impulse responses in the benchmark five-variable systems with each of hours, investment, and output for two subsample periods: the pre-1978 subsample period from 1955:Q1 to 1978:Q4 (the line with squares) and the post-1983 subsample period from 1983:Q1 to 2012:Q4 (the line with triangles). For comparison, the median impulse responses (the line with circles) and confidence intervals of the 16th and 84th quantiles (the shaded gray area) for the full sample period from 1955:Q1 to 2012:Q4 are also reported.

Table 1: Identification Strategy

TFP	Stock Price	Consumption	Real Interest Rate	All Other Variables
0	+	+	+	Unrestricted

Notes: This table shows the sign restrictions imposed to identify optimism shocks. 0 and + means the zero and positive sign restriction on the impact impulse response of a variable, respectively.

Table 2: The Share of Forecast Error Variance Attributable to Optimism Shocks in the Benchmark Five-Variable System

	Panel A: Adjusted TFP						Panel B: Non-Adjusted TFP					
	$h=0$	$h=4$	$h=8$	$h=16$	$h=24$	$h=40$	$h=0$	$h=4$	$h=8$	$h=16$	$h=24$	$h=40$
TFP	0.00 [0.00, 0.00]	0.02 [0.01, 0.05]	0.02 [0.01, 0.06]	0.05 [0.02, 0.10]	0.10 [0.03, 0.20]	0.17 [0.06, 0.34]	0.00 [0.00, 0.00]	0.07 [0.02, 0.15]	0.09 [0.02, 0.20]	0.10 [0.03, 0.23]	0.12 [0.03, 0.28]	0.17 [0.06, 0.35]
Stock Price	0.39 [0.10, 0.74]	0.44 [0.15, 0.75]	0.44 [0.14, 0.73]	0.39 [0.13, 0.65]	0.34 [0.11, 0.58]	0.26 [0.10, 0.48]	0.38 [0.10, 0.72]	0.44 [0.15, 0.74]	0.46 [0.16, 0.75]	0.44 [0.17, 0.71]	0.42 [0.17, 0.66]	0.38 [0.17, 0.59]
Consumption	0.18 [0.02, 0.54]	0.32 [0.10, 0.68]	0.36 [0.12, 0.71]	0.37 [0.13, 0.69]	0.35 [0.12, 0.65]	0.30 [0.10, 0.59]	0.15 [0.02, 0.46]	0.26 [0.08, 0.53]	0.29 [0.10, 0.56]	0.31 [0.11, 0.58]	0.30 [0.09, 0.58]	0.25 [0.07, 0.55]
Real Interest Rate	0.14 [0.01, 0.48]	0.15 [0.03, 0.44]	0.16 [0.04, 0.45]	0.16 [0.05, 0.43]	0.17 [0.06, 0.41]	0.19 [0.08, 0.38]	0.14 [0.01, 0.47]	0.13 [0.03, 0.41]	0.13 [0.04, 0.40]	0.14 [0.05, 0.37]	0.15 [0.06, 0.35]	0.16 [0.07, 0.34]
Hours	0.12 [0.01, 0.43]	0.24 [0.06, 0.58]	0.30 [0.07, 0.63]	0.28 [0.07, 0.60]	0.25 [0.07, 0.54]	0.24 [0.09, 0.47]	0.11 [0.01, 0.39]	0.18 [0.05, 0.46]	0.22 [0.06, 0.48]	0.22 [0.05, 0.48]	0.20 [0.06, 0.45]	0.19 [0.07, 0.41]
Investment	0.10 [0.01, 0.35]	0.21 [0.08, 0.56]	0.33 [0.11, 0.60]	0.34 [0.13, 0.59]	0.35 [0.13, 0.58]	0.35 [0.14, 0.56]	0.08 [0.01, 0.29]	0.15 [0.07, 0.29]	0.19 [0.09, 0.33]	0.22 [0.10, 0.36]	0.23 [0.11, 0.39]	0.24 [0.11, 0.41]
Output	0.08 [0.01, 0.27]	0.30 [0.08, 0.60]	0.36 [0.14, 0.63]	0.36 [0.17, 0.62]	0.35 [0.15, 0.61]	0.30 [0.12, 0.55]	0.05 [0.01, 0.18]	0.23 [0.09, 0.39]	0.28 [0.13, 0.47]	0.31 [0.14, 0.52]	0.32 [0.14, 0.54]	0.31 [0.13, 0.54]

Notes: This table reports the share of the forecast error variance attributable to optimism shocks identified in the benchmark five-variable system in which TFP is measured by adjusted TFP (Panel A) or non-adjusted TFP (Panel B). The share of the forecast error variance of each of investment and output is obtained in the system with each of investment and output in place of hours. 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: The Share of Forecast Error Variances of Labor Market Variables Attributable to Optimism Shocks

	$h = 0$	$h = 4$	$h = 8$	$h = 16$	$h = 24$	$h = 40$
Total Hours	0.12 [0.01, 0.43]	0.24 [0.06, 0.58]	0.30 [0.07, 0.63]	0.28 [0.07, 0.60]	0.25 [0.07, 0.54]	0.24 [0.09, 0.47]
Hours per Worker	0.13 [0.01, 0.45]	0.17 [0.04, 0.50]	0.18 [0.04, 0.52]	0.15 [0.04, 0.44]	0.14 [0.04, 0.35]	0.15 [0.05, 0.30]
Unemployment Rate	0.12 [0.01, 0.42]	0.27 [0.06, 0.63]	0.34 [0.10, 0.64]	0.34 [0.12, 0.60]	0.32 [0.12, 0.56]	0.29 [0.12, 0.51]
Labor Force Participation Rate	0.11 [0.01, 0.41]	0.11 [0.02, 0.39]	0.11 [0.02, 0.38]	0.11 [0.02, 0.37]	0.11 [0.02, 0.36]	0.12 [0.03, 0.37]
Job Finding Rate	0.13 [0.01, 0.46]	0.27 [0.08, 0.61]	0.33 [0.09, 0.65]	0.35 [0.09, 0.65]	0.34 [0.09, 0.64]	0.33 [0.10, 0.61]
Job Separation Rate	0.13 [0.01, 0.47]	0.18 [0.04, 0.52]	0.19 [0.04, 0.52]	0.20 [0.04, 0.50]	0.20 [0.05, 0.49]	0.20 [0.05, 0.47]
Job Vacancies	0.16 [0.02, 0.52]	0.28 [0.05, 0.64]	0.30 [0.06, 0.64]	0.28 [0.07, 0.60]	0.28 [0.08, 0.57]	0.26 [0.08, 0.53]
Vacancy-Unemployment Ratio	0.20 [0.02, 0.58]	0.32 [0.06, 0.67]	0.35 [0.08, 0.66]	0.35 [0.09, 0.64]	0.34 [0.09, 0.63]	0.33 [0.09, 0.61]

Notes: This table reports the share of the forecast error variance of each of eight labor market variables attributable to identified optimism shocks. Each share is estimated in the benchmark five-variable system, (Adjusted TFP, Stock Price, Consumption, Real Interest Rate, Each Labor Market Variable). 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.

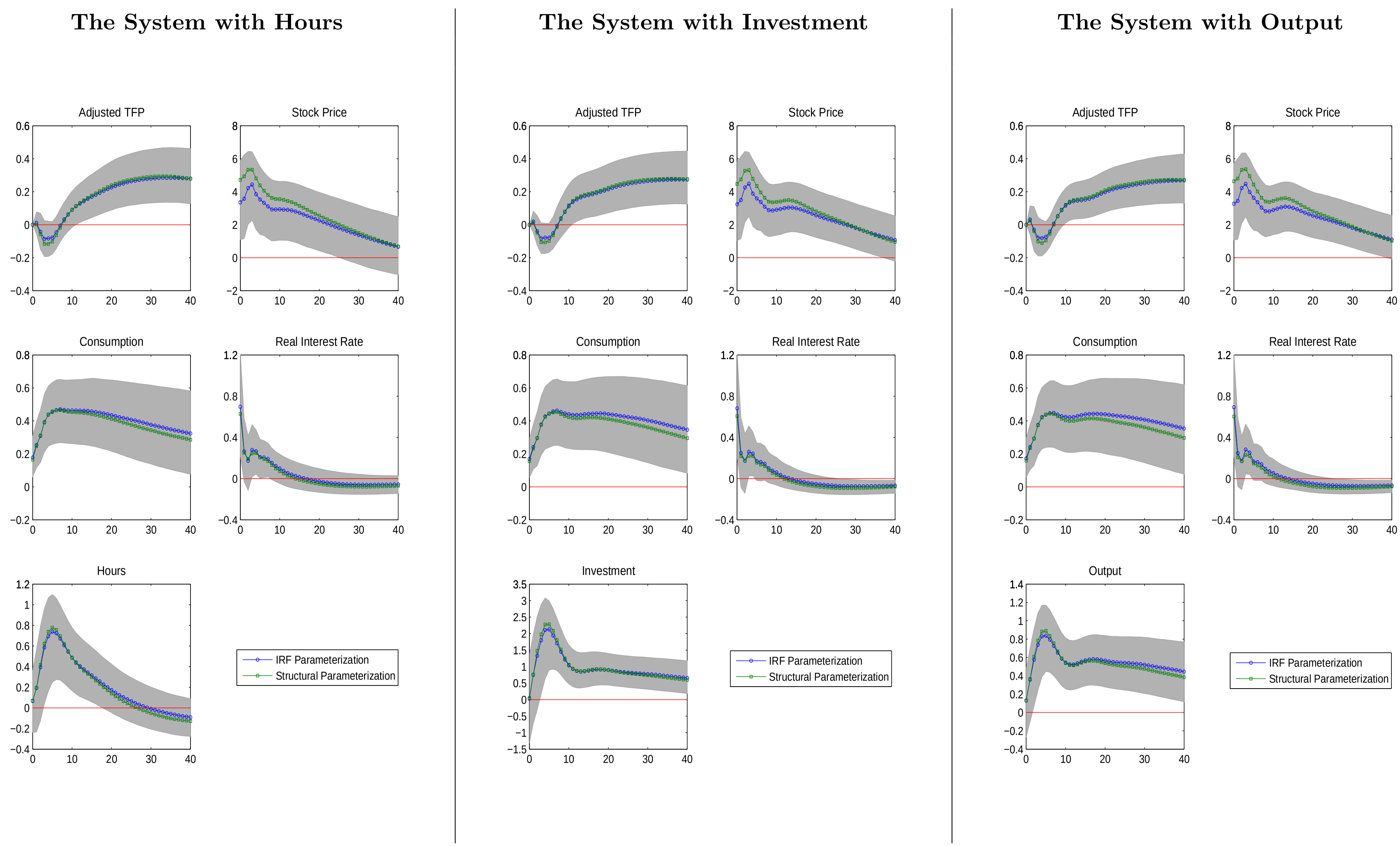
Table 4: Comparing with Other Studies

	Type of Identified Shocks	Restrictions on VAR Size	Lags between the Shock and Actual Changes in TFP
The current paper	Optimism Shocks	No	8-10 Quarters
Beaudry and Portier (2006)	News TFP Shocks	Yes	8-12 Quarters
Barsky and Sims (2011)	News TFP Shocks	No	1 Quarter
Barsky and Sims (2012)	Optimism/Confidence Shocks	Uncertain	1 Quarter (by assumption)
Levchenko and Pandalai-Nayar(2015)	Sentiment/Optimism shocks	No	N/A

Notes: This table compares the current paper with three related studies. See Section 4 for more details.

A.1 Appendix (not for publication)

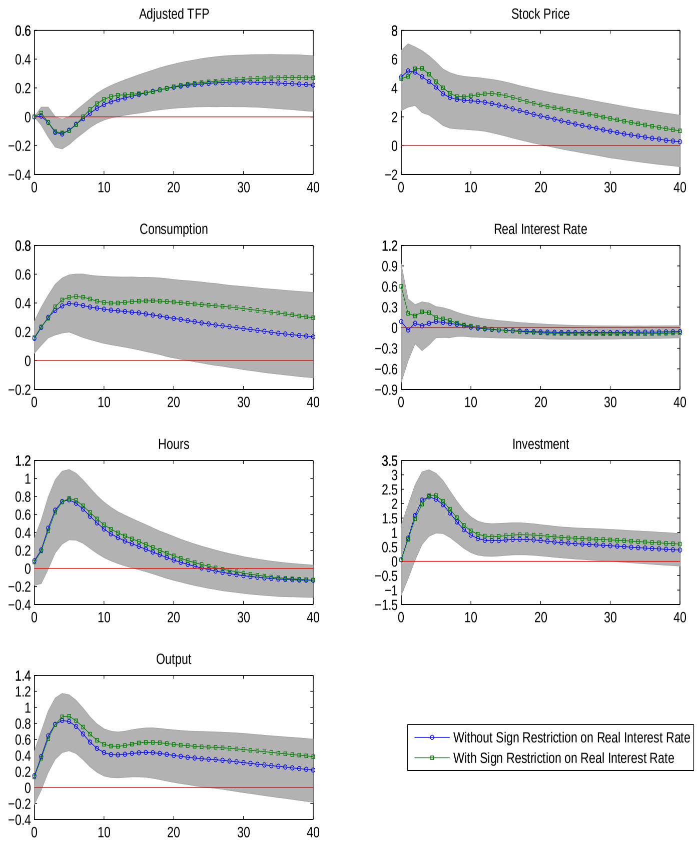
Figure A.1: Impulse Responses to an Optimism Shock in the Benchmark Five-variable Systems, Based on the Impulse Response Function Parameterization



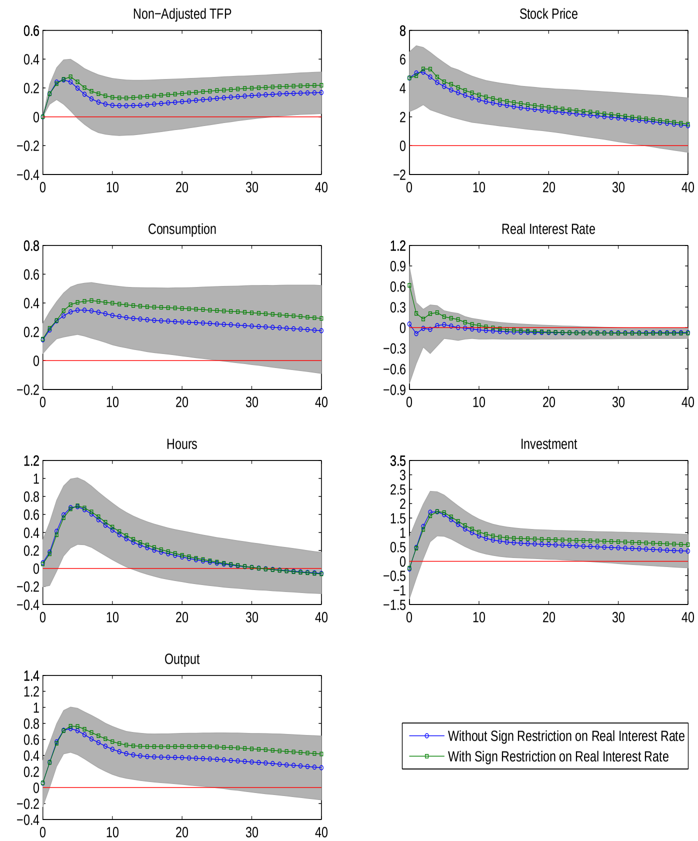
Notes: This figure has three panels each of which displays impulse responses to the identified optimism shock. The left, middle, and right panels show the impulse responses in the five-variable VAR systems with Hours, Investment, and Output, respectively. The Bayesian inference is based on the impulse response function (IRF) parameterization—see Section 3.4 for more details on this parameterization. The blue line with circles represents the median response and the shaded gray area represents the confidence interval with the 16th and 84th quantiles. For comparison, the corresponding median impulse responses based on the structural parameterization, which are those reported in the left panel of Figure 1, are also plotted.

Figure A.2: Impulse Responses to an Optimism Shock Identified without Sign Restriction on the Real Interest Rate

Adjusted TFP



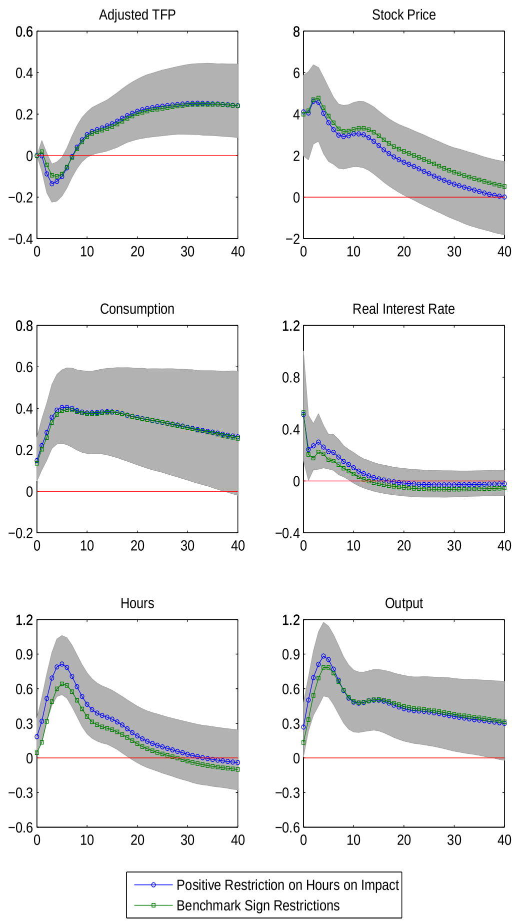
Non-Adjusted TFP



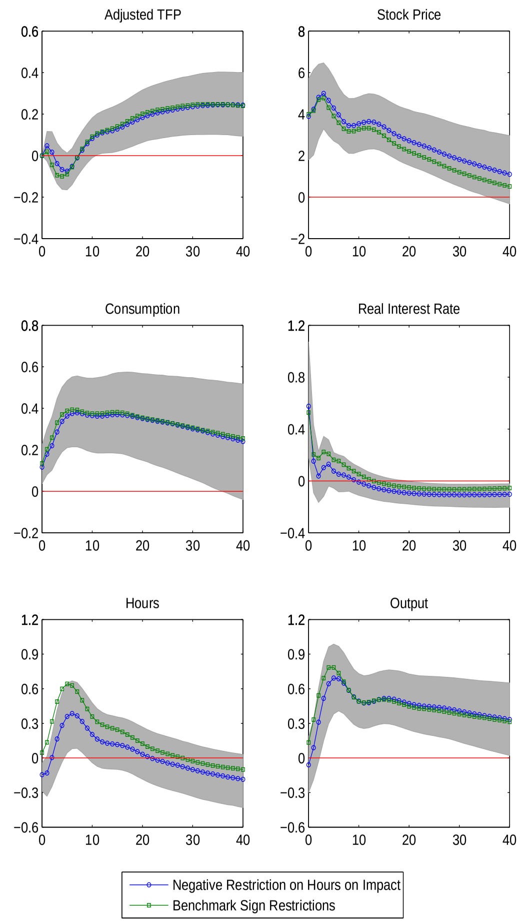
Note: This figure has two panels each of which displays impulse responses to the optimism shock identified without imposing the positive sign restriction on the real interest rate. The left (right) panel shows the impulse responses when TFP is measured by adjusted (non-adjusted) TFP series. In both panels, the impulse response of each of Investment and Output is estimated in the benchmark five-variable system with each of Investment and Output in place with Hours. The blue line with circles represents the median response and the shaded gray area represents the confidence interval with the 16th and 84th quantiles. For comparison, the median impulse responses to the optimism shock identified by imposing the positive sign restriction on the real interest rate, which are the green lines with squares, are also reported.

Figure A.3: Impulse Responses to an Optimism Shock in the Benchmark Six-variable System Imposing an Additional Restriction on Hours

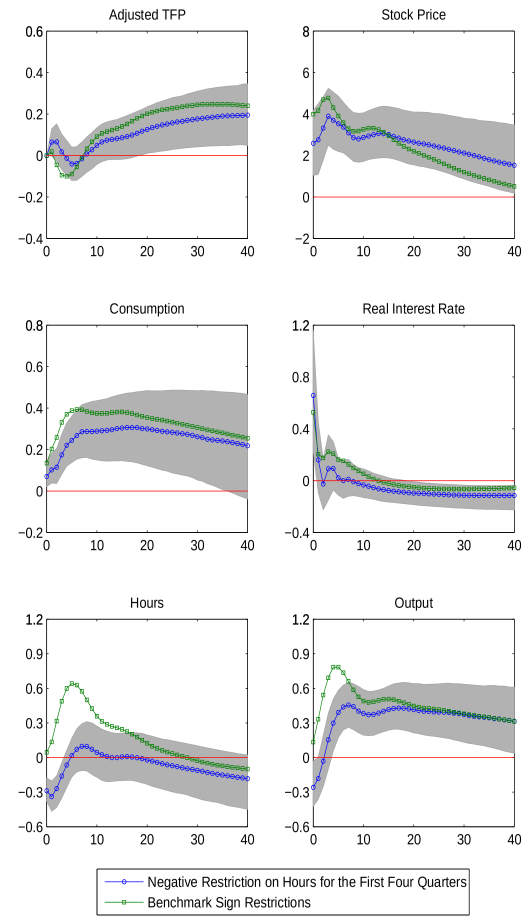
Positive Restriction on Hours



Negative Restriction on Hours I

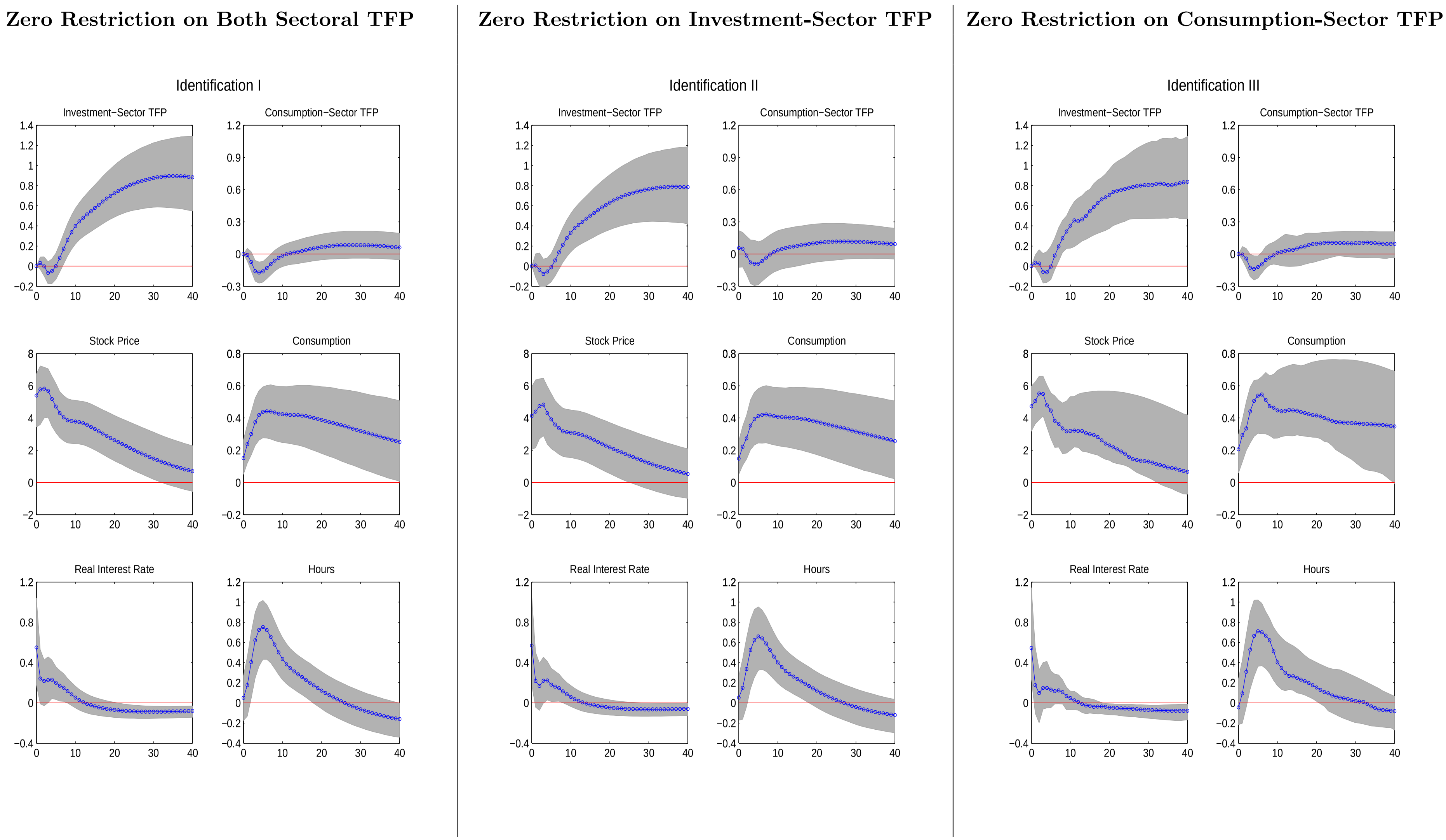


Negative Restriction on Hours II



Notes: This figure has three panels each of which displays impulse responses to the optimism shock in the six-variable system. Optimism shocks identified by imposing an additional restriction on hours. The left, middle, and right panels show the estimated impulse responses when imposing a positive sign restriction on hours on impact, imposing a negative sign restriction on hours on impact, and imposing negative sign restrictions on hours for the first four quarters, respectively. For comparison, the corresponding median impulse responses estimated using the benchmark restrictions on TFP, stock price, consumption and the real interest rate are also plotted.

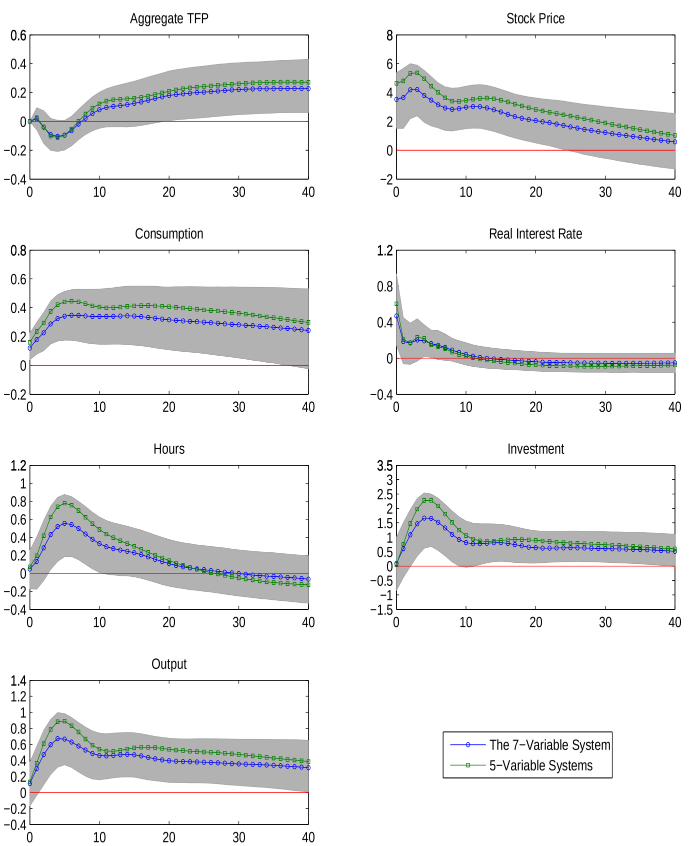
Figure A.4: Impulse Responses to an Optimism Shock in the Six-Variable System with Sectoral TFP



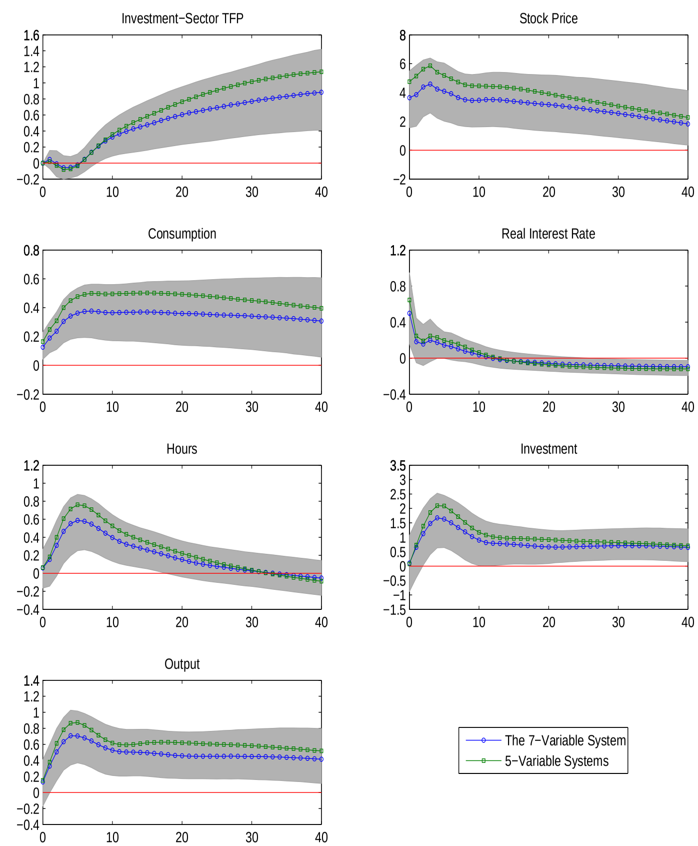
Notes: This figure has three panels each of which displays impulse responses to the identified optimism shock in the six-variable system with two sectoral TFP, (Investment-Sector TFP, Consumption-Sector TFP, Stock Price, Consumption, Real Interest Rate, Hours). The optimism shocks are identified by imposing the zero restriction on both sectoral TFP (the left panel), only on investment-sector TFP (the middle panel) or only on consumption-sector TFP (the right panel) as well as the positive sign restrictions on stock price, consumption, and the real interest rate.

Figure A.5: Impulse Responses to an Optimism Shock in the Seven-Variable System

Aggregate TFP



Investment-Sector TFP



Note: This figure has two panels each of which displays impulse responses to the optimism shock in the seven-variable system where TFP is measured by aggregate adjusted TFP series (the left panel) or investment-sector adjusted TFP series (the right panel). For comparison, the corresponding median impulse responses estimated from the five-variable systems, which are represented by the green line with squares, are also reported.