Distribution Agreement

Essays in Expectations-driven Business Cycles

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A dissertation submitted to the Faculty of the
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Abstract

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In the past decade or so, optimistic beliefs about the profitability of future technological innovations contributed immensely to economic activity. In this dissertation, I focus on the interplay between such beliefs, economic fluctuations, and technological innovations embodied in capital equipment.

In Chapter 1, I identify the main source of fluctuations in the labor share of income in the United States. Using the Maximum Forecast Error Variance (MFEV) approach, I find that the shock that explains most of the unpredictable fluctuations in the labor share is news about future technological progress embodied in capital. The shock induces a negative and overshooting response of the labor share. A standard Real Business Cycle model with a production function that has an elasticity of substitution less than one is capable of replicating the qualitative dynamics of the labor share.

In Chapter 2, my coauthor, Kaiji Chen, and I investigate the source of the fluctuations in aggregate variables and Total Factor Productivity (TFP). Using the MFEV approach, we sequentially identify two separate shocks — a news shock to the inverse of the relative price of investment and a news shock to TFP — and find that both shocks are highly correlated and account for over 50 percent of the Forecast Error Variance (FEV) of TFP. We use a standard two-sector business cycle model to argue that the close link between the two identified shocks is a consequence of spillover effect arising from diffusing innovations in investment-specific technology (IST) to TFP.

In Chapter 3, I explore whether mood swings, captured by optimism shocks, are a viable source of macroeconomic fluctuations as suggested by several empirical studies. Using a combination of sign and zero restrictions to identify simultaneously an optimism shock and an anticipated investment shock, I find that the anticipated investment shock emerges as the most plausible source of fluctuations. I isolate sequentially a TFP news shock and an IST news shock. I find that there is close link between the IST news shock and the anticipated investment shock while the optimism shock is no longer associated with the TFP news shock documented by some empirical studies vanishes.

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CHAPTER 1

THE CYCLICALITY OF THE LABOR INCOME SHARE AND THE IST NEWS SHOCK

Abstract

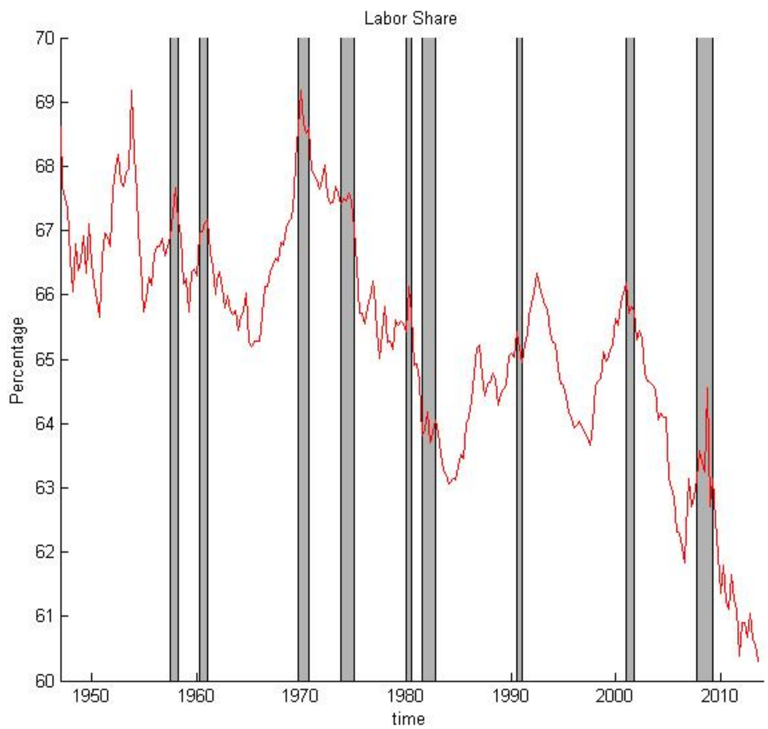
Fluctuations in the share of income that goes to labor have long been attributed to technological changes. To shed light on this relationship, I adopt a standard statistical approach to identify the shocks that explain most of the movements in the labor share of income in the U.S. over the period $1975-Q1$ to $2009-Q1$. I find that the shock that explains more than 55 percent of all unpredictable fluctuations in the labor income share in the U.S. over a 15-year forecast horizon can be interpreted as news about future technological progress embodied in capital. The news shock generates a negative and *overshooting* response of the labor share. To interpret these dynamics, I use a standard real business cycle model in which I adopt a constant elasticity of substitution instead of a Cobb-Douglas production function and find that an elasticity of substitution that is less than one is sufficient to replicate qualitatively the empirical dynamics of the labor share. Overall, these findings highlight that a simple framework with an elasticity of substitution less than one and a shock to anticipated future technological progress embodied in capital is sufficient enough to understand the empirical properties of the labor share.

Introduction

Since the pioneering work of Kaldor (1957), macroeconomic models have adopted a constant labor share as a well-known stylized fact of growth theory. Recently, however, the labor income share — the ratio of all payments to labor relative to output — has attracted the attention of labor and macroeconomists, who have attempted to rationalize an abrupt, and quite contested decline in its trend, which started in the early 1970s. A notable study by Karabarbounis and Neiman (2013) argues that this decline in the secular trend of the labor share is mostly attributable to the decline in the price of investment goods relative to consumption goods — a phenomenon often ascribed to advances in information technology and the computer age. This structural shift in the trend of the labor share merits a thorough investigation as it bears considerable implications for income inequality, the rise and limits of computerization, and standards of living. Additionally, the labor share exhibits significant short-run fluctuations, as indicated in Figure (1.1). For the period $1947-Q1$ to $2013-Q4$, the labor share oscillates between a maximum value of around 0.69 in $1970-Q1$ and a minimum value of 0.60 in $2013-Q4$, and it is about half as volatile as output. An early study by Solow (1958) argues that such fluctuations may be related to technological changes. Young (2199) makes a similar argument, demonstrating that a framework characterized by biased technological changes, such as exogenous changes in factor elasticities, is capable of generating the observed cyclical properties of the labor share.

In this paper, I propose that technological changes embodied in capital equipment are the main sources of fluctuations in the labor share. Using the Maximum Forecast Error Variance (MFEV) approach, I find that the shock that accounts for most of the forecast error variance in the labor share can be interpreted as an anticipated innovation in capital-embodied technology or an investment-specific technology (IST) news shock. Specifically, the identification process is built on

Figure 1.1: Labor income as a share of total income



Notes: The series is computed following the established methodology outlined in Gomme and Rupert (2004).

the theoretical assumption in Karabarbounis and Neiman (2013) — that only a limited number of factors have a permanent effect on the labor share of income. Consequently, in the first step, I adopt the MFEV approach in order to identify the shocks that explain most of the movements in the labor share of the U.S. over the period $1975-Q1$ to $2009-Q1$. This approach was proposed by Faust (2199) and refined by Uhlig (2003) as an alternative to other standard identification schemes that rely on short-run, long-run, and sign restrictions, among others. The basis of the approach is quite straightforward: rather than identifying a shock through the use of the above-mentioned restrictions and investigating its contribution to the variance of the k-step prediction error of the labor share of income, I will identify a limited number of shocks that explain much of the chosen variance for the share. In essence, this approach turns the standard identification methodology on its head. In the empirical literature, it is standard to first postulate a particular shock and investigate it theoretically in the hope of explaining much of the behavior of time series data. However, this alternative approach allows me to first examine the empirical evidence of the factors that actually move the time series and then attempt to provide an appealing theoretical interpretation for them. This approach is purely statistical and does not guarantee that a limited number of shocks will in fact account for a substantial amount of the movements in the share or that these shocks will have any structural interpretation.

Using post-World War II U.S. data over the period $1975-Q1$ to $2009-Q1$, I find that a single shock can explain more than 55 percent of all unpredictable fluctuations in the share over a 15-year forecast horizon. The impact response of the labor share to the shock is negative, suggesting that the labor share is counter-cyclical, as observed in its time series plotted in Figure (1.1). In addition, the share rises monotonically, reaches a maximum of 0.17 percent above its long-run average value in about 20 quarters, and returns to its mean after 40 quarters. This *overshooting* response of the labor share runs counter to predictions from standard real business cycle models with competitive input markets and a Cobb-Douglas production function. Similarly, real wage responds minimally and negatively on impact and then subsequently increases before returning to its long-run equilibrium. These dynamics indicate the potential presence of frictions in the labor market; a feature that might illuminate the counter-cyclical behavior of the labor share. Of particular interest is the response of the relative price of investment when attempting to ascribe a structural interpretation to the identified shock. On impact the response is nearly zero, but then the relative price gradually decreases and remains negative for more than 40 quarters. In fact, the relative price of investment never returns to its average and instead settles to a permanent long-run lower level. This decrease suggests that the identified shock captures the slow and permanent diffusion process of capital-embodied technological progress that is anticipated by market participants, an observation that symbolizes the news-driven business cycle theory and illustrates the conjecture that the news shock might be a supply shock. This hypothesis is further confirmed by the response of consumption, which rules out a demand shock as a candidate for the interpretation of the shock. Consumption permanently rises to a higher pre-shock level; a response that would be inconsistent with that of a demand shock.

To verify the interpretation that the single shock that drives the majority of the movements in the labor share might reflect news about future technological innovations embodied in capital, I identify in the second step the investment-specific technology news shock (or IST news shock) using the same statistical approach; however, I include the additional identifying restriction that the IST news shock is orthogonal to current innovations in the relative price of investment. This approach, which was first proposed by Barsky and Sims (2011), has been recently used by Ben-Zeev and Khan (2013) to show that the IST news shock is a major source of business cycle fluctuations. Therefore, I identify the IST news shock as the shock that accounts for much of the sum of the variance of the k-step prediction error for the relative price of investment over a forecast horizon of $k = 0, \ldots, 60$, such that the shock is orthogonal to current innovations in the relative price of investment. A look at the impulse response functions reveals that both shocks induce almost identical dynamics to the variables of the system even though they are identified using different approaches.

To interpret the dynamics of the labor share in response to the anticipated technological innovation embodied in capital equipment, I embed a constant elasticity of substitution (CES) production function into a standard neoclassical model and allow for an investment-specific technology that increases the efficiency with which investment goods are transformed into capital goods. After calibrating the model using 'common' values for the structural parameters of the model, I find that the simulated response of the labor share matches qualitatively that of the empirical dynamics. Specifically, in response to a one-standard deviation shock in the investment-specific technology, the labor share declines on impact, rises subsequently, and *overshoots* its pre-shock level by over 50 quarters. Such behavior is achieved with an elasticity of substitution less than one. The role of the IST news shock for the dynamics of the labor share works through the standard intratemporal and intertemporal decisions. To illustrate, suppose that the representative household anticipates an increase in the level of IST in the future. As a result, the future shadow value of installed capital increases and pushes up future marginal utility of consumption. Accordingly, future consumption must decrease. Under a log-power utility for consumption and leisure as in King, Plosser and Rebelo (1988a), the labor supply decision implies that future labor must rise intratemporally. In other words, the labor supply schedule is shifted outward and future wages decline while the rental rate of capital increases. The effects of an increase in the future rental rate of capital has implications for intertemporal decisions as well. Specifically, it implies that the opportunity cost of current leisure increases, and the household decides to supply more labor today — a decision that causes the real wage to decrease less than the increase in the current real rate of return. As a result, the ratio of the rate of return to wage increases, but such an increase generates a smaller corresponding increase in the labor-capital ratio because of the complementarity between labor and capital. Thus, the share of labor income relative to capital falls initially. However, when the innovation is realized, the ratio of the rate of return to wage falls and the labor share subsequently increases.

This paper contributes to the literature on the sources of the high-frequency movements in the labor share. An important result of the analysis is that it provides *new* empirical evidence establishing that the investment-specific technology shock is the main source of fluctuations of the labor share. This is contrary to the findings of Rios-Rull and Santaeulália-Llopis (2009) who use short-run restrictions to show that productivity shocks — identified as innovations in the Solow residual — induce an overshooting response to and account for 66.7 percent of variations in the labor share. The Solow residual is often used as a measure of technological progress; nonetheless, in the short-run, it is subject to change as a result of variations in capital utilization and may fail to reflect technological innovations. Consequently, such results might paint a misleading picture about the importance of technological change. However, the findings in the present analysis present a clear link between the labor share and technological progress. In addition, the results impose a clear discipline that may be used to discriminate between alternative classes of models for the labor share. For example, Choi and Rios-Rull (2008) explore the dynamics of the labor share to a productivity shock under a noncompetitive factor price setting similar to Merz (1995) and Andolfatto (1996). Although their model struggles to replicate the *overshooting* response of the labor share, it turns out that wage frictions are actually unnecessary for the cyclical properties of the labor share. To gauge the relative importance of wage friction, I extend the model in this analysis to include wage inertia, as in Blanchard and Gali (2005). The resulting model produces the same qualitative response of the labor share as in the benchmark model; however, the impact decline in the labor share is even smaller. This exercise suggests that wage frictions are, at worst, detrimental and, at best, inconsequential to the dynamics of the labor share. Thus, the simple model with only an IST news shock is sufficient enough to understand the empirical properties of the labor income share. Furthermore, the results point to an elasticity of substitution of less than one and indicate that labor and capital are complements. This hypothesis would be consistent with an economy that is composed of both routine workers and non-routine workers such that non-routine workers are made more productive by the efficiency of producing new capital goods. Routine workers execute tasks that are easily performed by computers (I take computers as an example of capital goods for simplicity); whereas non-routine workers perform tasks that require more cognitive skills and creativity — traits that cannot be easily simulated by computers. To illustrate, suppose that there is an innovation in the efficiency of computers.[1] Initially, routine occupations might decline as a result of the desire to accumulate more advanced computers. Yet, since the innovation is fairly new, non-routine workers might not immediately experience an increase in their productivity until they are familiar with the new technology. Thus, the initial share of total income that goes to both occupations might be low relative to the income going to the owners of the computers. However, as time progresses, non-routine workers quickly incorporate the new technology into their daily activities and experience a surge in their productivity. In that sense, computers bring to perfection the performance of non-routine workers who consider the advanced technology an essential component of their activity.

The empirical findings also contribute to our understanding of the role of embodied technological change in business cycle fluctuations. In addition to the findings of previous studies including, but not limited to, Fisher (2006), Jaimovich and Rebelo (2009), and Schmitt-Grohé and Uribe (2012), which argue for the importance of an investment-specific technology shock in business cycles, the results in this paper provide further evidence of its quantitative importance. However, the results appear to indicate that such technological innovations are anticipated by economic agents.

[1] An example of such an innovation is the Alteryx Designer, offered by the company Alteryx. It solves the process of blending data and creating analytics by delivering an intuitive workflow for data blending and advanced analytics. It empowers data analysts by combining data blending, predictive analytics, spatial analytics and reporting, and visualization and analytic applications into one workflow.

This hypothesis has been proposed by Beaudry, and Portier (2006), who find that the shocks that generate a market boom, while being contemporaneously unrelated to Total Factor Productivity (TFP), are highly correlated with the shocks that generate permanent changes in TFP. In contrast to their conclusion, the findings in this paper suggest that embodied technological change is the fundamental on which expectations are formed, a result that is also documented in Ben-Zeev and Khan (2013).

Finally, the results have major implications for theoretical models that seek to explain the disinflation induced by news shocks. Since the first and most influential empirical evidence in the news-driven business literature was offered by Beaudry, and Portier (2006), a great deal of empirical and theoretical work has been devoted to reconciling some of the well-known characteristics of business cycles with this theory. Although there has not been a consensus on the impact on quantity variables of good news about future economic fundamentals, one robust result has been prevalent across most empirical studies: news shocks are highly disinflationary. Consequently, few studies have attempted to provide a theoretical framework in order to shed light on the importance of news shocks for inflation dynamics. For instance, Barsky and Sims (2009) propose a simple New Keynesian model extended to include real wage rigidity and a monetary authority that responds to both an output gap and output growth. On the other hand, Christiano, Ilut, Motto and Rostagno (2010) argue that the disinflation is a consequence of the monetary authority moving the real interest rate in the wrong direction in response to a news shock. Notwithstanding the merits of these proposed frameworks, the results of the present study seem to suggest that an alternative structure; that is, an economy with a segregated labor market extended with sticky output prices, might be more suitable to understanding the relationship between inflation and a news shock.

In Section II, I describe the identification approach pursued in the paper. I provide a description of the data in section III, while the results of the analysis in terms of impulse responses and variance decomposition are presented in section IV. In section V, I lay down the theoretical framework used to interpret the results of the paper. Section VI examines the implications of the analysis and section VII contains robustness checks to gauge the sensitivity of the results to different specifications and alternative measurements of some of the variables of the system. Finally, summarizing comments are in section VIII.

Empirical Methodology

In this section, I briefly describe similar empirical approaches to estimate the dynamic effects of the shocks that are most important to the labor income share. Much of the discussion is borrowed from Kurmann and Otrok (2013). The first approach, Maximum Forecast Error Variance (MFEV), was proposed by Faust (2199) and refined by Uhlig (2003) to uncover the main shock(s) driving movements in real GNP. Rather than identifying a shock and investigating its contribution to the variance of the k-step prediction error of a target variable, which in this case is the labor share of income, I will identify a limited number of shocks that explain as much as possible the chosen variance for the labor share of income. In essence, I am looking for the main driving sources of fluctuations in the share. This approach is purely statistical and does not require that the chosen number of shocks will in fact account for a substantial amount of the movements in the share or that these shocks will have any structural interpretation. The second approach, which has been widely used in the empirical field to identify news shocks,[2] extends the technique by Uhlig (2003) to the relative price of investment as a target variable with the additional restriction that the identified shock is orthogonal to current innovations in the relative price of investment.

[2] See Barsky and Sims (2011), Kurmann and Otrok (2013), and Ben-Zeev and Khan (2013).

MFEV: VAR Basics

Most macroeconomic time series data is well approximated by a VAR(p) of the form:

$$Y_t = B_1 Y_{t-1} + ... + B_p Y_{t-p} + U_t, \tag{1.1}$$

where Y_t is a $(m \times 1)$ vector of observables at date t = 1-p,...,T; $B_i, i = 1, ..., p$ are coefficient matrices of size $(m \times m)$; and U_t is a $(m \times 1)$ vector of one-step-ahead prediction errors with variance-covariance matrix $E[U_t U_t'] = \Sigma$. Deterministic and exogenous terms are ignored to save on notation. The vector moving average representation of equation (3.1) is:

$$Y_t = C(L)U_t, \tag{1.2}$$

where $C(L) = [B(L)]^{-1} \equiv [I - B_1 L - ... - B_p L^p]^{-1}$.

Equation (3.2) can be estimated consistently using Ordinary Least Squares (OLS), which when conditional on Gaussian U_t and initial conditions, is equal to the maximum likelihood estimator (MLE). Identification of the structural shocks amounts to finding a mapping A_0 between the prediction errors U_t and a vector of mutually orthogonal shocks ε_t, such that $U_t = A_0 \varepsilon_t$ and the restriction $\Sigma = E[A_0 \varepsilon_t \varepsilon_t' A_0'] = A_0 A_0'$ is satisfied. This restriction is not sufficient, however, to identify A_0 because for any matrix A_0, there exists some alternative matrix $\tilde{A}$ such that $\tilde{A}Q = A_0$, where Q is an orthonormal matrix that also satisfies $\Sigma = \tilde{A}\tilde{A}'$. This alternative matrix maps U_t into another vector of mutually orthogonal shocks $\tilde{\varepsilon}_t$; that is, $U_t = \tilde{A}\tilde{\varepsilon}_t$. For some arbitrary matrix $\tilde{A}$ satisfying $\Sigma = \tilde{A}\tilde{A}'$, identification therefore reduces to choosing an orthonormal matrix Q.[3]

In the VAR literature, identification usually proceeds by identifying all m fundamental shocks, which leads to characterizing the entire A_0 matrix. This requires imposing $m(m-1)/2$ restrictions on A_0. For the present analysis, however, I identify at most n≤m fundamental shocks

[3]Possible candidates for $\tilde{A}$ are the choleski decomposition or the eigenvalue-eigenvector decomposition of Σ.

and therefore only need to characterize n≤m columns of the A_0 matrix. Under Uhlig's approach, this is equivalent to defining the n≤m columns of the orthonormal matrix Q, which explains much of the the sum of the variance of the k-step prediction errors for the labor share of income over a chosen horizon $k = \underline{k}, \ldots, \overline{k}$, where $\underline{k}$ and $\overline{k}$ represent the upper and lower bound, respectively. Formally, the k-step prediction errors of the j^{th} variable in Y_t, given all the data up to and including $t-1$, is given by:

$$Y_{j,t+k} - E_t Y_{j,t+k} = e_j' \left[\sum_{i=0}^{k-1} C_i \tilde{A} U_{t+k-i} \right], \tag{1.3}$$

where e_j is a column vector with 1 in the j^{th} position and zeros elsewhere. Suppose there are n < m columns of the orthonormal matrix Q that explain much of the sum of the variance of the k-step prediction error for the j^{th} variable in Y_t; in that case the approach solves

$$Q_n^* = \text{argmax} \;\; e_j' \left[\sum_{k=\underline{k}}^{\overline{k}} \sum_{i=0}^{k-1} C_i \tilde{A} Q_n Q_n' \tilde{A}' C_i' \right] e_j, \tag{1.4}$$

subject to

$$Q_n' Q_n = I. \tag{1.5}$$

A structural interpretation is then given to the identified Q_n^* by carefully analyzing the responses of the variables in Y_t to each column of Q_n^*. Such a process allows the narrowing of the number of shocks to the two or possibly one that are in fact needed to explain the target variable.

The second part of the empirical exercise consists of identifying a news shock about capital-embodied technological changes as performed by Ben-Zeev and Khan (2013). The crucial aspect in this approach is the assumption that the relative price of investment is characterized as following a process driven by two shocks. The first one is an unanticipated shock that has a contemporaneous impact on the level of the relative price of investment. This shock was introduced by Greenwood et al. (1997) and empirically identified using the relative price of investment via long-run restrictions in Fisher (2006). On the other hand, the second shock — an anticipated shock — is observed in advance by market participants, but affects the relative price of investment in the future. Consequently, in a VAR system with the relative price of investment ordered first, the unanticipated shock can be identified as the first column of a choleski decomposition of $\tilde{A}$ and the anticipated shock corresponds to the linear combination of the innovations that best explain future movements in the relative price of investment not accounted for by the unanticipated shock. While it is not always possible to satisfy both of these conditions, a restricted version of the approach offers a natural way to come as close as possible. Specifically, the approach finds column $q_{(1)}$ of Q that maximizes the sum of the FEV of the relative price of investment over a forecast horizon $k = \underline{k},...,\overline{k}$, subject to $q'q = 1$ and $q^{(1)} = 0$.[4]

Data and Specification

The empirical exercise uses U.S. data over the period $1975 - Q1$ to $2009 - Q1$. The baseline VAR consists of six variables. A careful selection of the variables of the system is imperative for uncovering the major sources of fluctuations in the labor share. The three key series are the price of investment goods relative to consumption goods, a measure of the labor share of income, and inflation. I also include hours worked and real wages as these variables form the basis for the construction of the labor share measure. Since I intend to gauge the importance of a news shock on the macroeconomy, I add real per capita consumption as another macroeconomic variable to explore the behavior of economic agents. The series are constructed as follows.

[4]The identified news shock is not restricted to be orthogonal to current innovations in TFP.

The price of investment relative to consumption goods corresponds to the ratio of the chain-weighted deflators for investment and consumption. The numerator is the National Income and Product Accounts (NIPA) deflators for durable consumption and private investment. However, Gordon (2199) and Cummins and Violante (2002) have argued that NIPA's quality adjustments may underestimate the rate of technological progress in areas such as equipment and software — an issue that can distort the measured contribution of IST changes to both growth and business cycles. Consequently, Gordon constructed the alternative price series for producer durable equipment, which is later updated by Cummins and Violante (GCV deflator hereafter). For the baseline model, I work with the NIPA deflators; nonetheless, I also check the robustness of the results with the use of the GCV deflator.[5]

Hours worked are constructed as the log of hours of all persons in the non-farm business sector divided by population, while real wages correspond to nominal compensation per hour in the non-farm business sector. The consumption measure is the per capita value of real personal consumption of nondurable goods and services. I use the corresponding chain-weighted deflators to obtain the real series. All per capita series are obtained by dividing the corresponding aggregate variables by the civilian non-institutional population aged sixteen and over, which is obtained from the Bureau of Labor Statistics.

The construction of the labor share is more intricate. Conceptually, the share is obtained by dividing the compensation of employees by gross value added, where gross value added is the sum of the following components: compensation of employees, corporate profits, rental income, net interest income, proprietors' income, indirect taxes less subsidies, and depreciation. At first glance, the computation seems straightforward. However, there has been a debate concerning the apportionment of proprietors' income. Proprietors' income includes both labor and capital components

[5] I would like to thank Pat Higgins from the Federal Reserve Bank of Atlanta for providing some help with the construction of the series.

and a concise decomposition is fundamentally ambiguous. Consequently, I follow the established methodology outlined in Gomme and Rupert (2199) and classify the compensation of employees as unambiguous labor income (UL), corporate profits, rental income, net interest income, and depreciation as unambiguous capital income (UK). I then compute the labor share as the ratio of unambiguous labor income to the sum of unambiguous labor and capital income.[6]

I estimate the baseline VAR system and the larger system in levels consisting of five lags of each variable. All the results are robust to adopting a four-lag specification. The results are obtained though OLS estimation and the one-standard deviation confidence bands are computed using bootstrapping, as suggested in Kilian (1998). In the baseline specification, I choose the lower and upper bounds of the forecast horizon to be respectively $\underline{k} = 0$ and $\overline{k} = 60$ in order to be consistent with Ben-Zeev and Khan (2013).

Results

In this section, I first extract the shocks that explain much of the sum of the variance of the k-step prediction error for the labor share. In fact, two shocks account for more than 85 percent of the variations in the share. Next, I attempt to provide a structural interpretation for the single shock among the two shocks that is the most important for fluctuations in the share. Specifically, I propose that the shock that explains most of the variations in the labor share reflects future changes in capital-embodied technology.

What Moves the Labor Share?

Applying Uhlig's approach, I derive the shocks that explain much of possible the sum of the variance of the k-step prediction error for the labor share over a forecast horizon of $k = 0, \ldots, 60$.

[6] I would like to thank Maggie Jacobson from the Federal Reserve Bank of Cleveland for providing some help with the construction of the series.

The choice of the forecast horizon is motivated by the desire to capture the factors that have a permanent impact on the labor share of income so as to remain consistent with the theoretical framework. Beaudry, Nam and Wang (2011) argue that the identification of technological innovations becomes ambiguous as the upper bound of the forecast horizon becomes shorter due to the potential contribution of other short-run factors. Consequently, I select a longer horizon to strengthen the identification process against any confusion with other potential shocks.

Since the statistical approach is based on the maximization of the variance of the prediction errors, I start the discussion of the results with the forecast error variance of the variables. The decomposition of the FEV indicates that only two shocks are necessary to account for over 85 percent of the unpredictable movements in the share, with the first shock as the most important.[7] Consequently, I focus my attention on the first shock. At this point, I do not ascribe a specific label to that single shock. Figure (1.2) displays the forecast error variance attributable to this shock. The upper panel of the figure indicates that the shock accounts for over 55 percent of the FEV in the labor share in 20 quarters. Furthermore, around 50 percent of the forecast error variance of the relative price of investment and wages and over 40 percent of the FEV of hours are attributable to this shock. The importance of the shock to the variations in hours worked points to supply shocks as potential candidates for the theoretical interpretation of the identified shock.

I attempt now to provide a structural interpretation for this shock by carefully examining the impulse response functions (IRF). Figure (1.3) displays the IRF of the variables of the baseline system to a 1 percent impulse in the shock. The impact response of the labor share to the shock is negative, suggesting that the labor share is countercyclical as seen in its time series plotted in Figure (1.1). The labor share then rises monotonically, reaches a maximum of 0.17 percent above its long-

[7]The other 15 percent is accounted for by other factors that I do not wish to uncover, as the main focus of the paper is to identify the main source of variations in the labor share; i.e., the most important shock. Also, as discussed in Uhlig (2003), there are multiple combinations of orthogonal shocks.

run average value in about 20 quarters, and returns to its mean after 40 quarters. This *overshooting* response of the labor share runs counter to predictions from standard real business cycle models with competitive input markets and a Cobb-Douglas production function. Similarly, real wage responds minimally and negatively initially and then subsequently increases before returning to its long-run equilibrium. These dynamics indicate the potential presence of frictions in the labor market, a feature that might illuminate the countercyclical behavior of the labor share. Of utmost importance is the response of the relative price of investment. On impact, its response is nearly zero, then the relative price of investment gradually decreases and remains negative for more than 40 quarters. In fact, the relative price of investment never returns to its average as it settles to a permanent long-run lower level. This decrease suggests that the identified shock captures a slow and permanent diffusion process of technological progress embodied in capital. Such an interpretation is explored by Ben-Zeev and Khan (2013), who identify a news shock about future capital-embodied technology. Similar to the approach in this paper, the authors use the relative price of investment as the target variable to identify an IST news shock and find that such a shock is important for business cycle fluctuations. In addition, they claim that capital-embodied technology, rather than capital-disembodied technology, is the main fundamental on which expectations are based. The response of the relative price of investment in the present analysis is nearly identical to that obtained by Ben-Zeev and Khan (2013).

It does appear that the identified shock is just a reflection of future changes in capital-embodied technology. Nonetheless, I would like to examine other potential interpretations before I proceed to exploring such a hypothesis. The leading candidates are labor supply shocks that create a wedge between the marginal rate of substitution of consumption for leisure and the marginal product of labor. These shocks have been argued to be major contributors to the business cycle movements of hours worked. However, Justiniano et al. (2010) finds that, although these shocks seem to dominate the fluctuations of hours at very low frequencies, they are quite irrelevant over the business cycle. In addition, Shimer (2009) expresses some skepticism about the idea that recessions are characterized as periods of widespread mono−polization of the labor market by workers. An observation of the impact response of wages appears to be consistent with their conclusions. Had the identified shock been a labor supply shock, wages would have exhibited a strong and positive impact response and not the paltry response displayed in Figure (1.3).

Other types of shocks to consider are demand shocks in the form of exogenous changes in government deficits and monetary policy. However, such shocks do not imply the type of permanent response in consumption that is observed in Figure (1.3). The response of consumption is strongly positive after 40 quarters and converges to a permanently higher level, allowing demand shocks to be safely ruled out as the probable shocks driving the variations in the share.

A third and very appealing type of shock to consider are factors that impact the marginal efficiency of transformation between investment goods and capital goods; or simply, marginal efficiency of investment (MEI) shocks. Such factors, which primarily consist of financial factors, have been shown by Justiniano et al. (2011) to be the main drivers of business cycle fluctuations. In the short-run, it is quite possible to envision a framework under which such factors could play a role in the movements of the relative price of investment. However, given the long forecast horizon chosen in this empirical exercise, it is almost unimaginable that such financial shocks would have a slow and permanent impact on the relative price of investment.

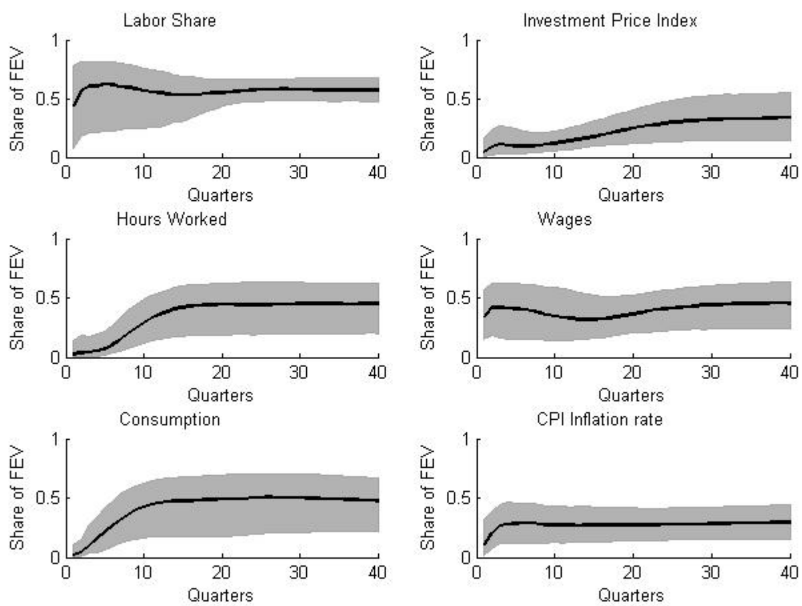
Structural Interpretation

To formally confirm that the shock that accounts for most of the FEV of the labor share is indeed a news shock to capital-embodied technological innovations, I identify an IST news shock using the same statistical approach with the additional restriction that the IST news shock is orthogonal to current innovations in the relative price of investment. This approach has been used recently by Ben-Zeev and Khan (2013) to show that the IST news shock is a major source of business cycle fluctuations. Specifically, an IST news shock is the shock that explains much of the sum of the variance of the k-step prediction error for the relative price of investment over a forecast horizon of $k = 0, \ldots, 60$, such that the shock is orthogonal to current innovations in the relative price of investment. Once again, I choose a longer forecast horizon to ensure that the identified shock reflects only technological progress.

Figure (1.4) displays the responses of the variables in the baseline VAR to a 1 percent impulse in the IST news shock. The identified IST news shock generates similar dynamics in the variables of the system as what is seen from the shock identified under Uhlig's approach. The labor share of income declines on impact, *overshoots* its pre−shock level, and only returns to its long-run equilibrium after 40 quarters. These dynamics are consistent with the findings of Rios-Rull and Santaeulália-Llopis (2009), who show that productivity shocks — identified through the use of short-run restrictions as innovations in the Solow residual — induce an overshooting response to and account for 66.7 percent of variations in the labor share. The Solow residual is often used as a measure of technological progress; although, in the short-run, it is subject to change as a result of variations in capital utilization and may fail to reflect technological innovations. Consequently, the response of the labor share to the IST news shock explored in this paper indicates a clearer link between the labor share and technological innovations. Similarly, the relative price of investment is zero on impact by restriction, then it slowly declines to a permanently lower level.

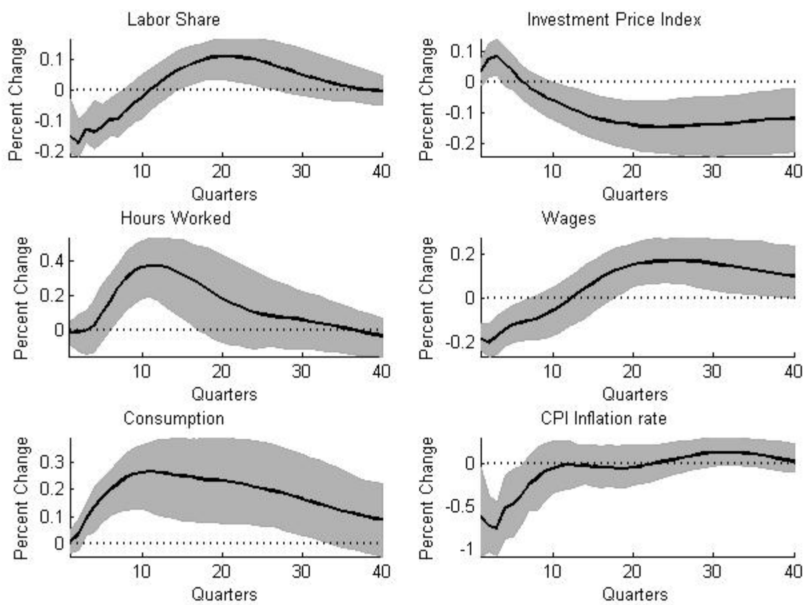
To solidify the notion that the shock identified under Uhlig's approach resembles an IST news shock, I plot the impulse responses of the variables in the baseline VAR to both shocks in Figure (1.5). The shocks induce almost identical dynamics to the variables of the system. The response of the labor share to both shocks is in fact almost indistinguishable. Another interesting graphical representation of the similarity between the two shocks is the plots of the time series of both shocks. Each series is obtained by estimating the baseline VAR using the appropriate estimation approach. The plot appears in Figure (1.6) and it demonstrates the affinity of the two shocks despite the fact that they are identified through different techniques. The correlation coefficient between the two identified shocks is 0.85.

Figure 1.2: Forecast error variance (FEV) to the single shock that accounts for most of the FEV in the labor share—Baseline VAR



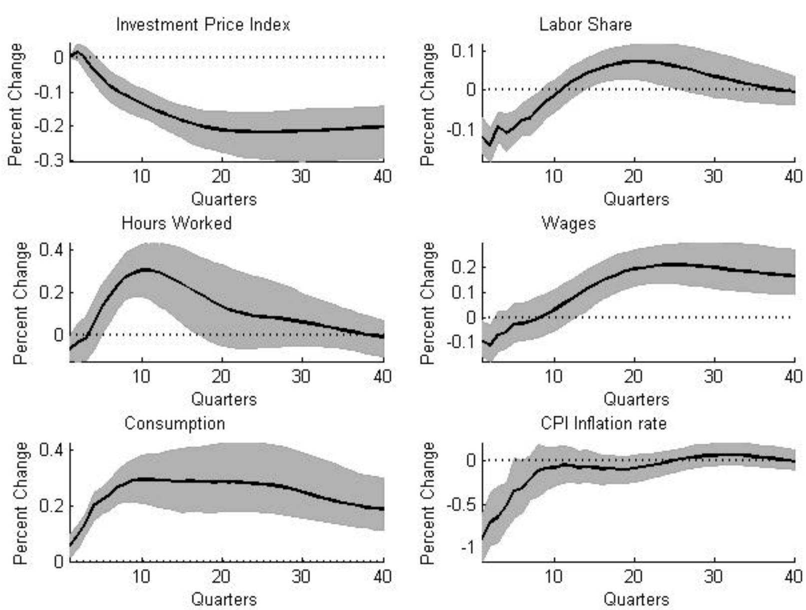
Notes: The solid line is the median FEV that is attributable to that shock in the Baseline VAR. The gray area represents the 16^{th} and 84^{th} confidence coverage obtained from bootstrapping the residuals.

Figure 1.3: Impulse response function (IRF) to the single shock that accounts for most of the FEV in the labor share—Baseline VAR



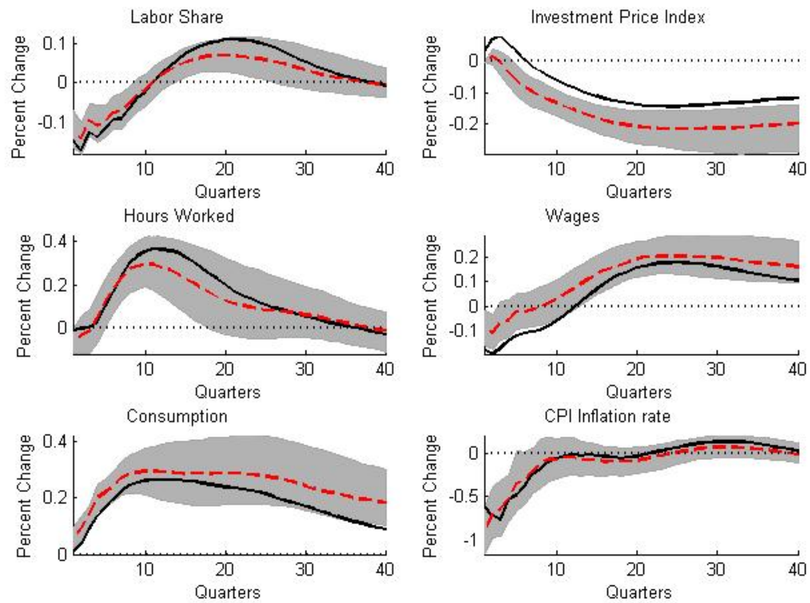
Notes: The solid line is the median IRF to a 1 percent impulse to that shock in the Baseline VAR. The gray area represents the 16^{th} and 84^{th} confidence coverage obtained from bootstrapping the residuals.

Figure 1.4: Impulse response function (FEV) to the IST news shock—Baseline VAR



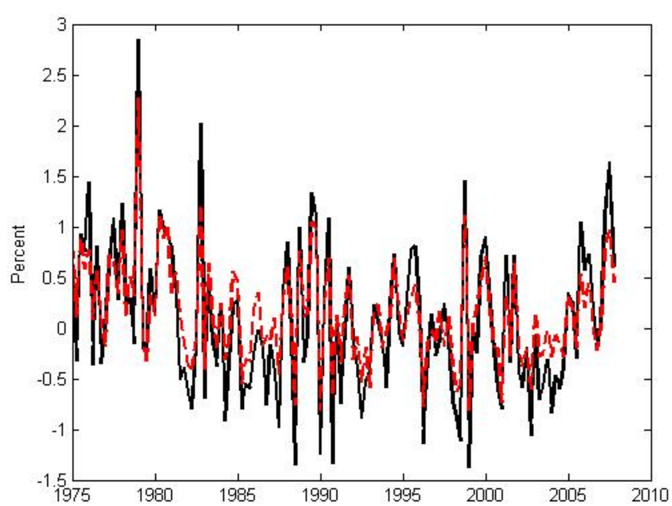
Notes: The solid line is the median IRF to a 1 percent impulse to the IST news shock in the Baseline VAR. The gray area represents the 16^{th} and 84^{th} confidence coverage obtained from bootstrapping the residuals

Figure 1.5: Impulse response function (IRF) to the IST news shock and the single shock that accounts for most of the FEV in the labor share—Baseline VAR



Notes: The solid line is the median IRF to a 1 percent impulse to the latter shock, while the dashed line represents the IRF to a 1 percent impulse to the former shock in the Baseline VAR. The gray area represents the 16^{th} and 84^{th} confidence coverage obtained from bootstrapping the residuals from the identification of the IST news shock.

Figure 1.6: Time series of the shocks



Notes: The solid line is the time series of the IST news shock, while the dashed line represents the time series of the single shock that accounts for most of the FEV in the labor share.

Theory

In this section, I attempt to interpret, from a theoretical point of view, the dynamic response of the labor share to the IST shock. I consider a standard Real Business Cycle (RBC) model with a single modification — I replace the Cobb-Douglas production function with a Constant Elasticity of Substitution (CES) production function. Formally, consider the following decentralized economy. A representative household owns both capital and labor that she supplies each period to a representative firm at a rental rate r_t and wage W_t, respectively. Moreover, the household is endowed with an investment-specific technology (IST) that converts one unit of final goods into V_t units of investment goods. Thus, the household's problem is:

$$\max_{C_t,K_t,N_t} E_0 \sum_{t=0}^{\infty} \beta^t \left[\log C_t + \varphi \frac{(1-N_t)^{1-\upsilon}}{1-\upsilon} \right],$$

subject to

$$\begin{aligned} C_t + I_t &= W_t N_t + r_t K_{t-1}, && (1.6) \\ K_t &= (1-\delta) K_{t-1} + V_t I_t, && (1.7) \\ \log(V_t) &= \rho_V \log(V_{t-1}) + \varepsilon_t^V + \varepsilon_{t-1}^V && (1.8) \end{aligned}$$

where E_0 is the expectations operator conditional on time t = 0 information; $\beta \in (0,1)$ is the discount factor; υ is the inverse of the Frisch elasticity of labor supply; and φ is a scaling factor.

The first order conditions are:

$$\begin{aligned} \frac{1}{C_t} &= \lambda_t, && (1.9) \\ \varphi (1-N_t)^{-\upsilon} &= W_t \lambda_t, && (1.10) \\ \mu_t &= \beta E_t \left[\lambda_{t+1} r_{t+1} + \mu_{t+1} (1-\delta) \right], && (1.11) \\ \mu_t &= \lambda_t / V_t, && (1.12) \end{aligned}$$

where λ_t and μ_t are simply the Lagrangian multipliers associated with constraints (1.6) and (1.7). Equation (1.12) implies that the shadow price of capital equals the shadow price of consumption λ_t multiplied by the marginal rate of transformation between investment and consumption $1/V_t$, which is equal to the relative price of investment (when there is an explicit capital producer). Combining the first order conditions above, we obtain the Euler equation and the intratemporal optimality condition:

$$\frac{1}{C_t V_t} = E_t \beta \frac{1}{C_{t+1}} \left[r_{t+1} + \frac{1}{V_{t+1}} (1-\delta) \right] \tag{1.13}$$

$$\varphi (1-N_t)^{-\upsilon} = W_t / C_t. \tag{1.14}$$

According to Equation (1.13), an anticipated increase in IST in the future would imply an increase in the future returns to capital r_{t+1}.

Forward iteration of the Euler equation and using the transversality condition gives the relative price of investment at period t as:

$$\frac{1}{V_t} = E_t \sum_{j=1}^{\infty} \beta^j (1-\delta)^{j-1} \frac{1/C_{t+j}}{1/C_t} r_{t+j}. \tag{1.15}$$

That is, the relative price of investment equals the presented discounted value of all future capital rents with the net-of-depreciation capital at period $t+j$ as $(1-\delta)^{j-1}$. Equation (1.15) implies that when the IST innovation is realized, such that the relative price of investment falls, future returns to capital will also fall as the supply of efficient capital in future periods increases.

Now I specify the firm's problem. The representative firms is endowed with a Constant Elasticity of Substitution (CES) technology to combine K_{t-1} and N_t into aggregate output Y_t. Specifically the firm's problem is:

$$\max_{K_{t-1}, N_t} \left[\alpha K_{t-1}^{\frac{\sigma}{\sigma-1}} + (1-\alpha) N_t^{\frac{\sigma}{\sigma-1}} \right]^{\frac{\sigma-1}{\sigma}} - r_t K_{t-1} - W_t N_t,$$

where $\sigma > 0$ is the elasticity of substitution between capital and labor.

The FOCs are:

$$\alpha \left(K_{t-1}/Y_t\right)^{-\frac{1}{\sigma}} = r_t, \tag{1.16}$$

$$(1-\alpha)\left(N_t/Y_t\right)^{-\frac{1}{\sigma}} = W_t. \tag{1.17}$$

Dividing Equation (1.16) by Equation (1.17) and reorganizing, we get:

$$\frac{N_t}{K_{t-1}} = \left(\frac{1-\alpha}{\alpha}\frac{r_t}{W_t}\right)^{\sigma}. \tag{1.18}$$

Accordingly, we have

$$\frac{W_t N_t}{r_t K_{t-1}} = \left(\frac{1-\alpha}{\alpha}\right)^{\sigma}\left(\frac{r_t}{W_t}\right)^{\sigma-1}. \tag{1.19}$$

Finally, the object of interest; i.e., the labor share of income is defined as the portion of output allocated to labor. Formally, it is equal to

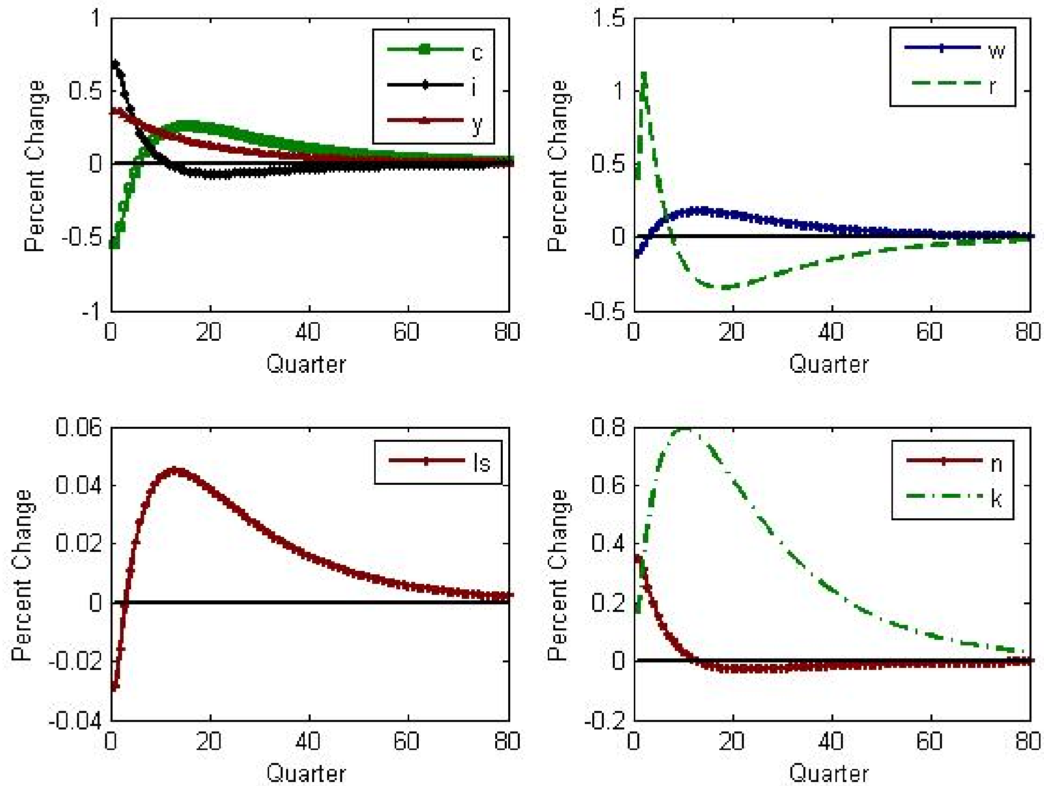
$$LS_t = \frac{W_t N_t}{Y_t}, \tag{1.20}$$

where LS_t denotes the labor share.

Decision rules are approximated via the log-linearization of the necessary conditions around the steady states of the model. The simulated paths of the variables are based on the following values of the structural parameters: $\beta = 0.99$, $\alpha = 0.45$, $\delta = 0.025$, $\sigma = 0.75$, $\nu = 2.5$, and $\rho_V = 0.95$. Most of the values are picked from existing studies and are consistent with the RBC literature.

The response of the labor share to a one-standard deviation shock in the investment-specific technology is depicted in Figure (1.7). I assume an anticipation period of one; that is, market participants receive information that the level of investment-specific technology will increase one period from today. Similar to its empirical counterpart, the labor share declines on impact and then *overshoots* its pre−shock level by over 50 quarters. Such a dynamic is obtained with an elasticity of substitution less than one. To illustrate, Equation (1.18) implies that when $\frac{r_t}{W_t}$ increases by one percent, labor-capital ratio will increase by less than one percent if the elasticity of substitution between capital and labor is less than one (complement). As a result, Equation (1.19) implies that the share of labor income relative to capital income falls initially. When the IST innovation is realized, however, $\frac{r_t}{W_t}$ tends to fall, which implies an increase in labor share when $\sigma < 1$. Mechanically, suppose that the representative household anticipates an increase in the level of IST in the future; i.e., V_{t+1} rises. From Equation (1.12), the shadow value of installed capital, $\mu_{t+1}V_{t+1}$, increases and pushes up the marginal utility of consumption, λ_{t+1}. As a result, according to Equation (1.9), future consumption, C_{t+1}, must decrease. Then, the intratemporal optimality condition, Equation (1.14), implies that future labor, N_{t+1}, rises at every level of wages as the labor supply schedule is shifted outward. Consequently, the real wage, W_{t+1}, declines and the rental rate of capital, r_{t+1}, increases. The effects of an increase in the rental rate of capital has implications for intertemporal decisions. Specifically, a rise in the future return to investment in capital implies that the opportunity cost of current leisure increases and the household decides to supply more labor today; that is, N_t rises. This decision pushes down the current real wage, W_t, and increases the real rate of return, r_t. As a result, the ratio of the real rate of return to real wage, $\frac{r_t}{W_t}$, increases. However, such an increase generates a smaller corresponding increase in the labor-capital ratio, $\frac{N_t}{K_{t-1}}$, because of the complementarity between labor and capital — this is seen in Equation (1.19). Thus, the share of labor income relative to capital falls initially. However, when the innovation is realized, the ratio of the real rate of return to real wage falls and the labor share subsequently increases. This mechanism highlights that the decline in the real wage caused by the outward shift of the labor supply to the IST news shock is the key result behind the decline of the labor share. In fact, the decline in the real wage is confirmed by its empirical dynamics expressed in Figure (1.3). Both anticipated and unanticipated neutral technology shocks would shift the labor demand curve, cause the real wage to increase, and make it very difficult for the labor income share to decline.

Figure 1.7: Impulse responses to a one-standard deviation shock in the one-period anticipated IST news shock in the RBC model



Implications

The statistical analysis implies that: 1) The shock that accounts for most of the fluctuations in the labor share can be interpreted as an IST news shock or news about future technological progress embodied in capital; 2) The IST news shock generates a negative and *overshooting* response of the labor share; and 3) Using a standard RBC model with a CES production function, I find that an elasticity of substitution that is less than one is an essential feature needed to replicate qualitatively the empirical dynamics of the labor share. In this section, I examine the implications of these results.

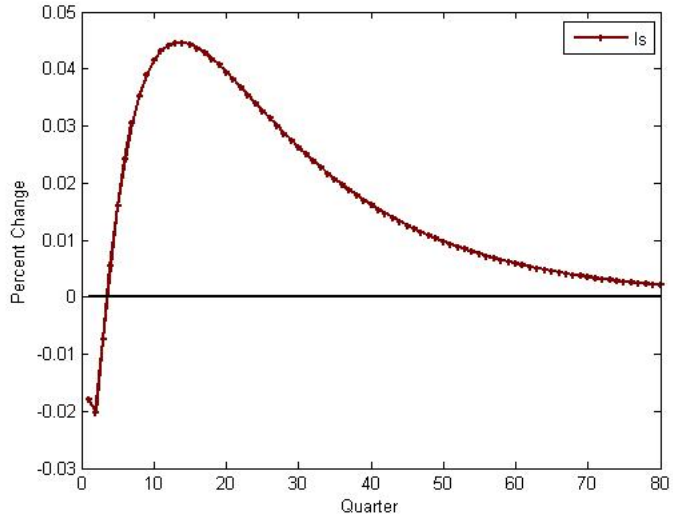
For one thing, the results impose a clear discipline that may be used to discriminate between alternative classes of models for the labor share. For example,Choi and Rios-Rull (2008) explore the dynamics of the labor share to a productivity shock under a noncompetitive factor prices setting similar to Merz (1995) and Andolfatto (1996). Their model with wage frictions struggles to replicate the *overshooting* response of the labor share and they reach the same conclusion with a CES production function. It turns out that wage frictions are actually unnecessary for the cyclical properties of the labor share. To gauge the relative importance of such wage friction, I extend the model in this analysis to include wage inertia, as in Blanchard and Gali (2005). Specifically, I replace the log-linearized version of Equation (1.14) with the following process:

$$w_t = (1-\rho_w)w_t^* + \rho_w w_{t-1}, \tag{1.21}$$

where w_t^* is the real wage obtained as in Equation (1.14) and ρ_w is the measure of the real wage rigidity. While this specification might be somewhat inconsistent with rational-expectation behavior, Blanchard and Gali (2005) demonstrate that it can be derived from explicit micro foundations.

I simulate the resulting model using the same approach as in the benchmark model. I set $\rho_w = 0.10$ to allow for a moderate level of wage inertia. The results of this experiment are presented in Figure (1.8). Qualitatively, the perturbed model produces the same response of the labor share as in the benchmark model; however, the impact decline in the labor share is even smaller, suggesting that wage frictions are, at worst, detrimental and, at best, inconsequential to the dynamics of the labor share. Thus, the simple model with only the IST news shock is capable of replicating the empirical properties of the labor income share. The explanation lies behind the fact that the IST news shock causes an outward shift of the labor supply curve and generates a decrease in the real wage. On the other hand, wage rigidities are necessary to counteract the outward shift in the demand curve that might occur as a result of an unanticipated neutral technology shock.

Figure 1.8: Response of the labor share to a one-standard deviation shock in the IST news shock in the RBC model with the wage inertia

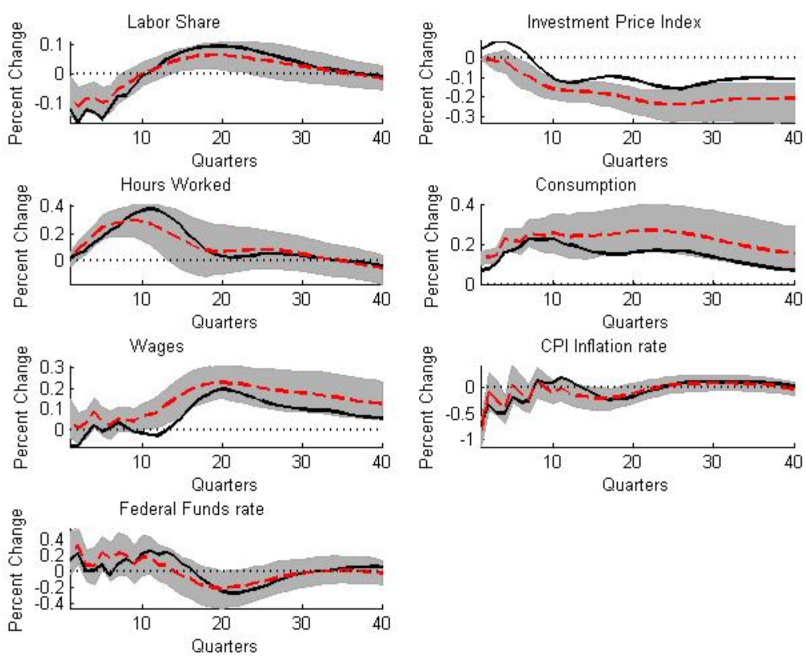


Notes: I set the measure of real wage rigidity $\rho_w = 0.10$.

Furthermore, the results point to an elasticity of substitution of less than one and indicate a complementarity between labor and capital. This implication is consistent with an economy in which the labor market is composed of routine and non-routine occupations and non-routine occupations become progressively more productive as a result of improvement in the efficiency of producing new capital goods. To illustrate, suppose that the economy features routine workers who execute tasks that are easily performed by computers (I take computers as an example of a capital good for simplicity). Non-routine workers, on the other hand, perform tasks that require more cognitive skills and creativity, traits that cannot be easily simulated by computers. When there is an innovation in the efficiency of computers, routine occupations might decline as a result of the desire to accumulate more advanced computers. Yet since the innovation is fairly new, non-routine workers might not immediately experience an increase in their productivity until they become familiar with the new technology. Thus, the initial share of total income that goes to both occupations might be low relative to the share going to creators and owners of the advanced technology. However, as time progresses, non-routine workers quickly incorporate the new technology into their daily activities and experience a surge in their productivity. In that sense, computers bring to perfection the performance of non-routine workers who consider advanced technology an essential component of their activity. A corollary of this mechanism is that the employment and wages of non-routine occupations should increase over time while the return to investment in capital should stagnate. In fact, Eden and Gaggl (2014) find that the share of employment and wages for high-skilled workers — given that high-skilled workers perform mostly non-routine tasks — have increased from 1979 to 2014. On the other hand, they document that the marginal product of information, communication, and computing technology (ICT) capital has declined during the same period. This finding lends support to the argument that capital and labor are complements.

In addition, the results have major implications for theoretical models that seek to explain the disinflation induced by news shocks. The most robust result that has emerged so far from the news-driven business cycle is that news shocks are highly disinflationary. Few studies have attempted to provide a theoretical framework to shed light on the importance of news shocks for inflation dynamics. Barsky and Sims (2009) propose a simple New Keynesian model extended to include a real wage rigidity and a monetary authority that responds to both an output gap and output growth. On the other hand, Christiano, Ilut, Motto and Rostagno (2010) argue that the disinflation is a consequence of the monetary authority moving the real interest rate in the wrong direction in response to a news shock. The results of the empirical analysis tend to support the notion that news shocks induce a disinflation. On impact, inflation declines by more than 0.5 percent and remains negative for over 10 quarters. Given the relationship between inflation and the labor share implied by the NKPC, the negative response of inflation is consistent with a contemporaneous decline in the labor share as shown in Figure (1.4). Unlike other proposed frameworks in the literature, the results of the present study seem to suggest that an alternative structure — such as an economy with a segregated labor market extended with sticky output prices — might be more suitable to understanding the relationship between inflation and news shocks. Furthermore, I include the federal funds rate among the variables of the system to examine the connection between inflation and the actions of monetary policy authorities. The impulse responses of the variables in this larger system are displayed in Figure (1.9). The dynamics of the labor share, the relative price of investment, hours, wages, consumption, and inflation are similar to those seen in the baseline VAR. In addition, the federal funds rate increases in response to the IST news shock, suggesting that monetary policy is contractionary.

Figure 1.9: Impulse response function (IRF) to the IST news shock and the single shock that accounts for most of the FEV in the labor share—larger VAR



Notes: The solid line is the median IRF to a 1 percent impulse to the latter shock, while the dashed line represents the IRF to a 1 percent impulse to the former shock in the larger VAR with nominal variables. The gray area represents the 16^{th} and 84^{th} confidence coverage obtained from bootstrapping the residuals from the identification of the IST news shock.

Robustness Check

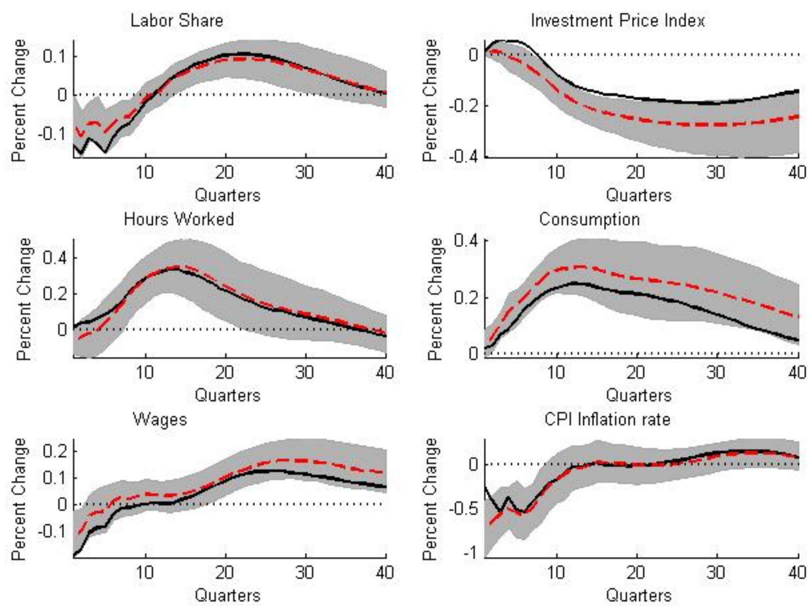
In this section, I conduct robustness checks to verify that the results are not sensitive to an alternative measure of the relative price of investment.

Alternative Measure of the Relative Price of Investment

I perform the same exercise as in Section 1.2 using the relative price of investment measured with the GCV deflator instead of the NIPA deflator. Specifically, I identify the share shock as the shock that explains as much as possible the variance of the k-step prediction error for the labor's share over a forecast horizon of $k = 0, \ldots, 60$ and I identify the IST news shock using the same statistical approach with the additional restriction that IST news shocks are orthogonal to current innovations of the relative price of investment.

The results appear in Figure (1.10) and show that the impulse responses are close to those in the baseline VAR. In addition, the correlation coefficient between the two identified shocks is 0.8306.

Figure 1.10: IRF to the IST news shock and the single shock that accounts for most of the FEV in the labor share—GCV deflator



Notes: The solid line is the median IRF to a 1 percent impulse to the latter shock, while the dashed line represents the IRF to a 1 percent impulse to the former shock when the NIPA deflator is replaced with the GCV deflator. The gray area represents the 16^{th} and 84^{th} confidence coverage obtained from bootstrapping the residuals from the identification of the IST news shock.

Conclusion

In this paper, I set out to identify the shocks that explain most of the movements in the share of income that goes to labor in the U.S. over the period $1975-Q1$ to $2009-Q1$ in order to provide some guidance to theoretical models attempting to understanding the cyclical properties of the labor share. Adopting statistical approaches by Uhlig (2003) and Ben-Zeev and Khan (2013), I find that the single shock that explains the majority of all unpredictable fluctuations in the share over a fifteen−year forecast horizon can be interpreted as an IST news shock: a shock that explains much of the sum of the variance of the k-step prediction error for the relative price of investment over a forecast horizon of $k = 0,...,60$, such that it is orthogonal to current innovations in the relative price of investment.

Both shocks induce similar dynamics on the labor share, the relative price of investment, hours worked, real wages, consumption, and inflation and account for a sizable portion of the FEV in these variables. The plots of the time series of the shocks indicate that the labor share shock and the IST news shock are highly correlated with a correlation coefficient of 0.85. Most importantly, the IST news shock generates a negative and *overshooting* response of the labor share. Using a standard RBC model with a CES production function, I find that an elasticity of substitution less than one is the essential feature needed to replicate qualitatively the empirical dynamics of the labor share. Overall, the results of this paper suggest that an environment with labor and capital as complementary inputs might be a more suitable framework to understanding the cyclical properties of the labor share and its subsequent implications for the dynamics of inflation.

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CHAPTER 2

INVESTMENT-SPECIFIC TECHNICAL CHANGES:

THE SOURCE OF ANTICIPATED TFP FLUCTUATIONS

by Kaiji Chen[1] and Edouard Wemy[2]

Abstract

News shocks to TFP have been argued to be important drivers of U.S. business cycles. This paper assesses the quantitative importance of news about investment-specific technical changes in anticipated future TFP fluctuations. To this end, we sequentially identify two news shocks with the maximum forecast error variance approach: news shocks to TFP and news shocks to the inverse of the relative price of investment. We show in a model with IST spillover that the correlation of these two empirically identified news shocks is a useful measure of the importance of news about IST improvements in expected future TFP fluctuations. Using post-war U.S. data, we find that these two news shocks are almost perfectly collinear when both are identified to capture the long-run variations in the corresponding variables. Moreover, these two news shocks can explain a significant, and surprisingly similar, fraction of the business-cycle fluctuations in other important macro variables. Our findings suggest that news about embodied technological changes is an important driver of anticipated future TFP fluctuations and U.S. business cycles.

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Introduction

Following Beaudry, and Portier (2006), recent empirical studies have emphasized news shocks to Total Factor Productivity (TFP) as important driving forces of business cycles. Intuitively, a diffusion process of technology foreseen by economic actors would lead to an expectation of future TFP increase. Nonetheless, various factors—other than news about technological changes—may influence agents' anticipations about future TFP fluctuations.[3] This raises a critical question: What is the quantitative importance of news about future technological opportunities for the anticipated TFP fluctuations? Moreover, given the importance of technological innovations, are anticipated future TFP fluctuations driven by news on technical changes embodied or disembodied in equipment capital?[4] Answers to both questions would sharpen our understanding of the role of technological changes in business cycle fluctuations.

This paper therefore assesses the quantitative importance of news on investment-specific technical ("IST" henceforth) changes in anticipated future TFP fluctuations. To this end, we identify sequentially two news shocks with the maximum forecast error variance approach ("MFEV" henceforth): news shocks to TFP and news shocks to the inverse of the relative price of investment. We then construct a model where an IST diffusion process influences expected future TFP fluctuations via spillover. We show that, in this model, the correlation of these two news shocks, when sequentially identified to best explain the long-run movements of the corresponding variables, can be fruitful in distinguishing the quantitative importance of innovations to the IST diffusion process in anticipated future TFP fluctuations.

Using post-war U.S. data, we find that these two identified news shocks are almost perfectly

[3] For example, Chen and Song (2013) show both theoretically and empirically that variations in financial frictions on capital allocation translate into anticipated TFP fluctuations. Other shocks that may impact economic agents' expectations about future TFP include research and development shocks, investment shocks, and reallocative shocks.

[4] Technical improvements embodied in equipment have been argued to be the source of fast U.S. productivity growth in the late 1990s.

collinear if both are identified by maximizing the sum of the FEVs of the corresponding variable over a finite, but sufficiently long, horizon. Moreover, both shocks incur almost identical impulse responses (“IRFs” henceforth) on various macro variables and can explain a significant fraction of the fluctuations of consumption, hours worked, and output over business cycles. Our findings suggest that news about embodied technological changes is an important driver of anticipated future TFP fluctuations and U.S. business cycles.

To explore the source of anticipated TFP fluctuations, we first map the identified news shocks under the MFEV approach into the primitive shocks in a two-sector model featured by IST spillover.[5] In our model, the permanent IST innovation, which follows a diffusion process, is a news shock as it influences the level of future, not contemporaneous, investment-specific technology. A novel feature of our model is that such permanent IST shocks affect the expected future TFP of not only the capital-producing sector, but also the consumption sector via spillover. This captures the idea that investment-specific technology is general purpose. Accordingly, when sequentially identified to best explain the long-run movements of TFP and the relative price of investment, both of these two news shocks contains the permanent innovation to IST as the common driving force. This renders the correlation of the two empirically identified news shocks a useful measure of the extent to which IST innovations contribute to anticipated future TFP fluctuations.

The quasi-identity of our identified news shocks suggests that news about IST changes is one main source of anticipated future TFP fluctuations. In particular, the impact response of TFP to the news shock to the inverse of the relative price of investment (“PC” henceforth) is essentially zero. In the long run, by contrast, the news shock to PC can explain more than 50 percent of TFP fluctuations. Similarly, while PC responds little on impact to the news shock to TFP, more than 70 percent of its long-run variations can be explained by the news shocks to TFP. This high correlation

[5]The spillover effect in our model may, in reality, correspond to both technological spillover and unmeasured complementary investment in intangible capital to accommodate the use of information-intensive equipment and software.

between the two identified news shocks is very robust to adding more variables, different lags, alternative measures of investment deflators, alternative empirical specification, and alternative TFP series.

As a further test whether our identified news shocks capture an IST diffusion process, we examine the impact of different forecast horizons chosen under the MFEV approach on the correlation between the two identified news shocks. We find that if the lower bound for the forecast horizon is sufficiently large—say, close to 40 quarters—then the perfect collinearity between the two identified news shocks is very robust to the upper bound of the forecast horizon. By contrast, with a zero lower bound for the forecast horizon, the correlation drops monotonically as the upper bound for the forecast horizon becomes smaller. Behind such a drop in correlation is that the identified news shock to TFP is sensitive to the forecast horizon chosen under the MFEV approach. All these findings suggest that the news shock to TFP under the MFEV approach would truly capture the slow technical diffusion process only if it is identified by maximizing the FEV of TFP at or around a sufficiently long forecast horizon.

Our paper contributes to the VAR-based literature on news shocks from several perspectives.[6] First, to our knowledge, we are the first to establish the empirical linkage between anticipated TFP fluctuations and news about IST changes. Despite the difference in identification strategies, most studies in this literature implicitly identify the news shocks to TFP with the news shocks to neutral technology.[7] Recent studies on news shocks to TFP have incorporated shocks to the relative price of investment into a SVAR, but most of them assume that the shocks to the relative price of

[6]Important papers in this literature include, among others, Beaudry, and Portier (2006), Beaudry and Lucke (2010), Fisher (2010), Schmitt-Grohé (2010), Barsky and Sims (2011), Beaudry, Nam and Wang (2011), Ben-Zeev and Khan (2013), Kurmann and Otrok (2013), and Kurmann and Mertens (2014).

[7]One exception is Nam and Wang (2014), who argue that anticipated TFP fluctuations in the long-run are driven by investment sector TFP. However, as our model in Section III shows, investment sector TFP can be driven by either neutral or investment-specific technology shocks.

investment and TFP news shocks are orthogonal to each other.[8] Such an assumption is inconsistent with the empirical findings of Schmitt-Grohé and Uribe (2011), who demonstrate that TFP and the relative price of investment are cointegrated. Our model of IST spillover shows that permanent IST innovations may underlie the long-run variations of both TFP and the relative price of investment. And our empirical findings of the quasi-identity of these two sequentially identified news shocks suggest that news about IST changes are important drivers of anticipated TFP fluctuations and U.S. business cycles.

Second, our empirical findings shed light on the caveat of choosing the forecast horizon under the MFEV approach to identify the TFP news shocks. We show that our identified news shocks to TFP would truly capture the slow diffusion process of technology only when the upper bound of the forecast horizon is sufficiently large with the zero lower bound, or if the FEV of TFP is maximized at a finite but long horizon. Our results, therefore, echo the findings of two recent papers: In Beaudry, Nam and Wang (2011), the TFP news shocks identified under the MFEV approach are highly correlated with the optimism shocks identified under sign restriction; and such high correlation is robust if the forecast error variance of TFP is maximized at some finite long horizon or if the upper bound is large enough. Similarly, in Nam and Wang (2014), the impulse responses of aggregate variables to news shocks to aggregate TFP are almost identical to news shocks on investment sector TFP, identified by maximizing the FEV of investment-sector TFP under a sufficiently long forecast horizon. Furthermore, our paper is the first to show theoretically why such a high correlation might happen when the forecast horizon chosen under the MFEV approach

[8]For example, in their identification scheme 2 (ID2), Beaudry and Lucke (2010) assume that shocks to the relative price of investment have no permanent impact on TFP. Under this assumption, shocks to the relative price of investment are better interpreted as other shocks to the price of investment (such as relative markup or input cost shocks to investment) than IST. Fisher (2010) adopts a similar identification strategy and finds that news shocks to TFP and permanent IST shocks are equally important in explaining the business cycles. One exception is Schmitt-Grohé (2010), who suspects the news shocks to TFP identified under the approach of Beaudry and Lucke (2010) to be investment-specific shocks. The focus of Schmitt-Grohé (2010) is, however, how to empirically distinguish anticipated TFP shocks from anticipated investment-specific shocks, rather than viewing the investment-specific shock as a potential source of anticipated TFP fluctuations.

is sufficiently long.

Our findings also contribute to the understanding of the role of IST shocks in business cycles. Fisher (2006) argues that permanent IST shocks are the main sources of business cycles. In addition, Jaimovich and Rebelo (2009) and Schmitt-Grohé and Uribe (2012) argue for the importance of IST news shocks in business cycles. This view is further supported by the empirical findings of Ben-Zeev and Khan (2013), who use an identification approach similar to the one adopted in this paper. Our results not only provide additional support for the quantitative importance of anticipated IST shocks for business cycles, but also suggest that such permanent innovations to IST enhance aggregate productivity with a delay. More importantly, we go a step further to show that the mechanism for IST shocks to impact the business cycle, as our empirical findings suggest, may well be different from the conventional mechanism.[9] The crucial role of news on future IST improvements in anticipated TFP fluctuations suggests that one potentially important channel for IST news shocks to drive business cycles may be through influencing prospecting about future aggregate productivity. Such a channel, we argue, may lead to a positive comovement between consumption and investment and a negative comovement between stock price and the relative price of investment, as our empirical impulse responses show. Thus, our findings provide new insight on the role of IST news shocks in business cycles.

In addition, our empirical findings provide additional support for the role of investment-specific technical changes as general purpose technology. It has long been argued that investment-specific technical changes are important sources of productivity growth in the U.S. Using industry-level data, Cummins and Violante (2002) and Basu, Fernald and Oulton (2004) find that improve-

[9]In conventional business-cycle models (e.g., (Greenwood, Hercowitz and Krusell, 1997) and (Fisher, 2006), IST shocks directly impact the efficiency of investment-good production and the shocks are amplified by hours worked and capital utilization. Therefore, IST shocks lead to a capital deepening throughout the economy and increase labor productivity. However, from the neoclassical perspective, there is no reason to expect growth in TFP (adjusted for capital utilization) outside of the capital producing sector.

ments in IST, such as information communication technology, contributed to productivity growth in the late 1990s in essentially every industry. Accordingly, both papers argue that investment-specific technical changes represent a general purpose technology. Moreover, Jorgenson, Ho, Samuel and Stiroh (2007) show that much of the total factor productivity gain in the 2000s originated in industries that are the most intensive users of information technology. Beyond its role for long-run productivity growth, several papers study the implications of technical diffusion in business cycles.[10] However, most studies in this literature consider only unanticipated technical diffusions.[11] A common issue with this specification, as pointed out by Jovanovic and Lach (1997), is that general purpose technology takes longer to spread than the length of typical business cycles.[12] By contrast, our findings suggest that changes in IST as a general purpose technology may be important drivers of business cycles via influencing the economic actor's expectation about future aggregate productivity.

The remaining sections are structured as follows. In Section II, we present our empirical strategy. In Section III, we provide a model with IST diffusion and spillover and show how the news shocks identified in our VAR are mapped into the primitive shocks in this model. In Section IV, we present the data and discuss the specifications of VAR. In Section V, we provide our empirical results estimated with post-war U.S. data. Section VI concludes.

[10] See, for example, Lippi and Reichlin (1994), Jovanovic and Lach (1997), Andolfatto and MacDonald (1998), and Rotember (2003).

[11] One exception is Comin, Santacreu and Gertler (2009), in which innovation shocks resemble news about future productivity growth via costly technology adoption.

[12] For example, Jovanovic and Lach (1997) find that with the unexpected arrival of embodied technological innovations, a business-cycle model calibrated to the empirical diffusion speed tends to over-predict (under-predict) the autocorrelation of GDP at low (high) frequencies.

Empirical Approach

In this section, we sequentially identify two news shocks: a news shock to aggregate TFP and a news shock to the inverse of the relative price of investment. Our identification scheme is fairly standard: we adopt a variant of Uhlig (2003) approach to extract the shock that best explains the sum of the FEVs over a given horizon for a given target variable *i*, where *i* is either TFP or PC. As our next section shows, anticipated long-run fluctuations in both TFP and the inverse of the relative price of investment could be driven by a common shock, that is, a news shock to the investment-specific technology. Therefore, we use this approach sequentially, rather than simultaneously, to identify these two news shocks. Similar to Ben-Zeev and Khan (2013), we identify a news shock that (in a statistical sense) best explains future movements in PC and is orthogonal to its contemporaneous movements. We only impose one zero impact restriction, that is, the restriction on PC.[13] The TFP news shock is identified in a similar fashion, with TFP being the target variable. Barsky and Sims (2011) identify TFP news shocks by maximizing the sum of the FEVs of TFP over a certain forecast horizon. In contrast, we will identify the TFP news shock under various forecast horizons and explore its correlation with the identified news shock to PC under these various cases as a further test whether our identified news shocks truly capture an IST diffusion process.

Different from previous empirical studies in this literature, at this stage, we are agnostic about the economic interpretation of our identified news shocks. In the next section, we provide a model of IST spillover to offer a structural interpretation of the news shocks identified in this section. We show that the impact response of TFP (PC) to our identified news shock on PC (TFP), as well as the correlation of the two news shocks identified in this section, can uncover the source of anticipated TFP fluctuations, which is the focus of the paper.

[13] Our results are robust to the identification of news shocks using two zero restrictions.

We start by assuming that we already have the reduced-form moving average (Wold) representation for the VAR system in level

$$\mathbf{Y}_t = C(L)\,\mathbf{u}_t,$$

where Y_t is a $m \times 1$ vector of variables at time t, $C(L) = I + \sum_{i=1}^{\infty} C_i L^i$ is a polynomial in the lag operator L, and u is a $m \times 1$ vector of reduced-form innovations with a variance-covariance matrix given by Σ.

Assume that there exists a linear mapping between reduced-form and structural shocks

$$\mathbf{u}_t = A\varepsilon_t.$$

The key restriction on A is that it satisfies $\Sigma = E\left[A\varepsilon_t\varepsilon_t' A'\right] = AA'$. This restriction is not sufficient to identify A, since for any matrix A there exists an alternative matrix $\tilde{A}$, such that $A = \tilde{A}Q$, where Q is an orthonormal matrix. This alternative matrix $\widetilde{A}$ maps u_t into another mutually orthogonal structural shock $\widetilde{\varepsilon}_t$, $u_t = \tilde{A}\widetilde{\varepsilon}_t$. Hence, for some arbitrary matrix $\tilde{A}$ satisfying $\tilde{A}\tilde{A}' = \Sigma$, identification is equivalent to choosing an orthonormal matrix Q.

Assuming that there exists a shock that does not have an immediate impact on variable y_i, but becomes an important factor in y_i over the forecast horizon $\left[\underline{k}, \overline{k}\right]$, we can identify such a shock by finding a column q_1 of Q that explains the sum of the FEVs of variable y_i in Y_t over the horizon $\left[\underline{k}, \overline{k}\right]$. Specifically, we solve the following maximizing problem, given the Cholesky decomposition of Σ, $\tilde{A}$:

$$q_1 = argmax \;\; q_1' S q_1 \equiv q_1' [\sum_{k=\underline{k}}^{\bar{k}} \sum_{l=0}^{k} \tilde{A}' C_l' (e_i e_i') C_l \tilde{A}] q_1 \tag{2.1}$$

subject to

$$q_1' q_1 \;\; = \;\; 1 \tag{2.2}$$

$$q_1^{(1)} \;\; = \;\; 0, \tag{2.3}$$

where S is the sum of the variances of the k-step ahead forecast error of the i^{th} variable in Y_t over the forecast horizon $k \in [\underline{k}, \overline{k}]$.[14] The first constraint guarantees that q_1 is a unit-length column vector that belongs to an orthonormal matrix, while the second restriction imposes that the news shock has no contemporaneous effect on the level of TFP or PC. Uhlig (2003) shows that this problem can be written as a quadratic form in which the non-zero portion of q_1 is the eigenvector associated with the largest eigenvalue of the $(m-1) \times (m-1)$ submatrix of S.

Mapping News Shocks into Primitive Shocks

How would our identified news shocks uncover the importance of news about IST improvement in anticipated future TFP fluctuations? To answer this question, in this section we first present a business-cycle model that incorporates an IST diffusion process together with other permanent and transitory disturbances to TFP and PC. This model nests different assumptions concerning the effect of IST innovations and diffusion on the productivity of the rest of the economy. We then map our identified news shocks into the primitive shocks. In this model, we show that the correlation of the two news shocks, when identified to best explain the long-run fluctuations of TFP and PC, respectively, can be fruitful in measuring the quantitative importance of news about IST changes in anticipated future TFP fluctuations.

Our framework is a two-sector neoclassical model. The model has the standard assumptions about the economic environment, except for the primitive shocks underlying the sectorial TFP, which we return to in the next section. Specifically, one sector produces consumption goods C, and the other sector produces investment goods I. Both sectors produce output by combining capital K and labor L with the Cobb-Douglas production function F and common factor shares, but with separate Hicks-neutral TFP parameters, TFP^C and TFP^I. Firms in both sectors are perfectly com-

[14] Note that when we refer to the FEV at horizon k, we mean the $(k+1)$-step ahead FEV. For example, FEV at $k = 0$ refers to the one-quarter ahead FEV.

petitive and face the same input prices. In addition, both capital and labor can be freely reallocated across sectors. Under these assumptions, the relative TFP of the investment sector equals the inverse of the relative price of investment goods, making the two-sector model isomorphic to the one-sector business cycle model with IST. Later, we explore the relationship between the relative TFP and the relative price of investment when any of the above assumptions is violated.

Moreover, in this framework, the measured sectorial TFP is equivalent to the sectorial technology. Therefore, we define $\Phi_t \equiv TFP_t^I / TFP_t^C$ as the investment-specific technology or so-called embodied technology. Implicitly, TFP^C represents productivity applied to both sectors, while Φ applies only to the investment goods-producing sector. In standard business-cycle models, changes in TFP^C originate from changes in the neutral technology. However, in our framework, embodied technologies may impact TFP^C via spillover.

Using consumption goods as the numeraire, the aggregate value-added is defined as the sum of consumption and the efficient units of investment:

$$Y_t = C_t + I_t \cdot P_t^I / P_t^C,$$

where P_t^I / P_t^C is the relative price of investment, expressed as the ratio of the investment deflator P_t^I to consumption deflator P_t^C. It is easy to show that, under the assumption of perfect competition, common factor shares, and input prices across sectors, the relative TFP of the investment sector equals the price of consumption goods relative to investment goods:

$$\log TFP_t^I / TFP_t^C = \log P_t^C / P_t^I \equiv \log PC_t, \tag{2.4}$$

where, for notational simplicity, we denote $P_t^C / P_t^I \equiv PC_t$.

In practice, however, there is no reason to expect that equation (2.4) holds exactly. First, the equality of factor shares across sectors does not hold (see, for example, (Valentinyi and Herrendorf, 2008)). Second, with factor adjustment costs, factor prices may differ across sectors. More generally, different sectors may involve different markups of price above marginal cost. In Appendix 2A, we show in a generalized version of the two-sector model that these departures from the standard assumptions described above result in a wedge between the relative price of investment and the relative TFP of the investment sector.[15] Finally, factors driving a wedge between firm-level TFP and technology include returns to scale, markup, capital utilization, and allocative efficiency, which implies a further wedge between the relative technology and the relative price.[16]

We therefore introduce a wedge between PC and the investment-specific technology, which—without loss of generality—consists of both a permanent and a stationary components:

$$\log PC_t = \log \Phi_t + \varpi_t + \omega_t. \tag{2.5}$$

In equation (2.5), ϖ_t (ω_t) is a permanent (stationary) component of the relative price of investment and both components are orthogonal to Φ_t. Specifically, $\varpi_t = \varpi_{t-1} + \upsilon_{1t-1}$, υ_{1t} is i.i.d and $\upsilon_{1t} \sim N\left(0, \sigma^2_{\upsilon_1}\right)$; $\omega_t = \rho^{\omega}\omega_t + \upsilon_{2t}$, υ_{2t} is i.i.d and $\upsilon_{2t} \sim N\left(0, \sigma^2_{\upsilon_2}\right)$. For generality, we allow the non-IST permanent shock to PC, υ_1, to have a zero impact effect on PC.[17] Equation (2.5) implies that even long-run fluctuations in PC can be affected by shocks other than IST changes. However, as Basu, Fernald, Fisher and Kimball (2013, Figure 2) found, PC and the relative TFP of the investment sector track each other fairly well over long periods of time, though these two series can diverge in the short run and medium run. Therefore, it is expected that permanent shocks to IST play the dominant role in the long-run fluctuations in PC, which is confirmed later by our empirical evidence.

[15] See also Justiniano, Primiceri and Tambalotti (2011), Basu, Fernald, Fisher and Kimball (2013), "BFFK" henceforth), and Ben-Zeev and Khan (2013) for a discussion.

[16] Using annual data, which contain rich industry-level details on output and intermediate-input flows and on industry investment, Basu, Fernald and Kimball (2006) construct a measure of purified aggregate technology changes. However, for the U.S. economy, these data are not available at quarterly levels. Accordingly, later in our empirical section, we use the utilization-adjusted TFP measures, which correct for a quantitatively important wedge between the measured relative TFP and the underlying relative technology.

[17] Adding the unanticipated permanent non-IST shocks to PC in equation (2.5) would not affect our interpretation of the news shocks to PC, since we impose zero impact restriction in our empirical identification.

Next, we explore the source of aggregate TFP fluctuations. Define aggregate TFP as the standard Solow residual, $TFP_t \equiv Y_t / F(K_t, L_t)$. Following the literature, we use the standard Divisia definition of aggregate output.[18] In Appendix 2B, we show that the log difference of aggregate TFP can then be proxied by a weighted sum of the log difference of sector-specific TFP.[19]

$$\Delta \log TFP_t = \left(1 - w^I\right) \Delta \log TFP_t^C + w^I \Delta \log TFP_t^I, \tag{2.6}$$

where $w^I \equiv P^I I / \left(P^C Y\right)$ is the share of investment goods in the aggregate value added at period t. Given the definition of Φ, changes in aggregate TFP can be rewritten as

$$\Delta \log TFP_t = \Delta \log TFP_t^C + w^I \Delta \log \Phi_t. \tag{2.7}$$

Without loss of generality, we can further normalize the levels of $\log TFP_t$, $\log TFP_t^C$, and $\log \Phi_t$ at period 0 to be zero.[20] Since equation (2.7) holds for all period t, it implies that

$$\log TFP_t = \log TFP_t^C + w^I \log \Phi_t. \tag{2.8}$$

According to (2.8), shocks to Φ may influence aggregate TFP via two channels. First, the direct effect, which is captured by the second argument on the right side of (2.8). The existence of the direct effect is simply because—under the Divisia definition of aggregate output— the current-period relative price for investment is used to compute the growth rate of real aggregate output, which takes into account the quality change of investment. Accordingly, some of the fluctuations in IST will be identified as fluctuations in aggregate TFP.[21]

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[18] See Jorgenson and Griliches (1967), Basu and Fernald (2002), and Fernald (2012) for the application of Divisia indices to the measurement of productivity changes. In practice, a continuous-time Divisia index can be proxied by the discrete Tornqvist index.

[19] The Divisia definition of aggregate output is consistent with the National Income and Product Accounts (NIPA) definition of real output. The NIPA adjusts aggregate output for equipment quality and real output are chain-linked: Each year the current prices are used as a base in estimating the rate of growth to the following year.

[20] Consistent with this normalization, in the empirical section, we back out levels of the logs of TFP and PC from the corresponding data on log difference by setting the initial levels of the logs of TFP and PC to zero.

[21] See Greenwood, Hercowitz and Krusell (1997) for a discussion.

Second, improvement in Φ may lead to improvement in productivity applied to all sectors, TFP^C, which we call the spillover effect. Such a spillover effect was emphasized in the literature on IST as general purpose technology and was found to be empirically important for productivity growth using either industry- or firm-level data.[22] The focus of this paper is to quantify the contribution of news on IST improvements to anticipated future TFP fluctuations via the spillover effect.

The above general setup of the model nests several specific cases about the role of IST shocks in aggregate TFP fluctuations. As we will show below, these various cases differ in their assumptions regarding the specifications of Φ_t and TFP_t^C. We now provide a specification to nest an IST diffusion process, together with other transitory and permanent shocks to either Φ_t or TFP_t^C.

IST Diffusion and Spillover

Consider a specification where innovations to IST involve a diffusion process that does not immediately increase productivity.[23] For comparison, the neutral technology includes a similar diffusion process. In addition, we allow temporary disturbances to both types of technology. This delivers the following data-generating process for IST and TFP of the consumption sector:

$$\begin{aligned}
\log \Phi_t &= \sum_{i=0}^{\infty} d_i^I \eta_{1,t-i}^I + \nu_t^I, && (2.9)\\
\log TFP_t^C &= \sum_{i=0}^{\infty} d_i^N \eta_{1,t-i}^N + \nu_t^N + \alpha \sum_{i=0}^{\infty} d_i^I \eta_{1,t-i}^I, && (2.10)\\
d_i^J &= 1-(\delta_J)^i, 0 \leq \delta_J < 1,\ J = I \text{ or } N, && (2.11)\\
\nu_t^J &= \rho^J \nu_{t-1}^J + \eta_{2,t}^J,\ 0 \leq \rho^J < 1,\ J = I \text{ or } N, && (2.12)
\end{aligned}$$

[22]For example, Cummins and Violante (2002) argue that technological improvement in equipment and software initiated in the 1970s and 1980s brought about acceleration in productivity growth in every industry in the 1990s, consistent with the idea that information technology represents a general-purpose technology. Similarly, Basu, Fernald and Oulton (2004) find that industries with high ICT capital growth rates in the 1987-2000 period had faster acceleration in TFP growth in 2000.

[23]The diffusion process is adopted in Beaudry, and Portier (2006) for aggregate TFP.

where $\eta_1^I \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{\eta_1^I}\right)$, $\eta_1^N \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{\eta_1^N}\right)$, $\eta_2^I \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{\eta_2^I}\right)$, and $\eta_2^N \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{\eta_2^N}\right)$.[24] By construction, all primitive shocks are orthogonal to each other.[25]

The process $D_t = \sum_{i=1}^{\infty} d_i^I \eta_{1,t-i}^I$ is a diffusion process, since an innovation η_1^I is restricted to have no immediate impact on Φ, i.e., $d_0^I = 0$. δ_J measures the diffusion speed in that a higher δ_J implies a slower diffusion. In general, the diffusion speed for the two types of technology can be different, i.e., $\delta_I \neq \delta_N$. Moreover, the effect of η_1^I on Φ is assumed to grow over time $\left(d_i^I \leq d_{i+1}^I\right)$ and the long-run effect is normalized to 1. Thus, the innovation η_1^I contains news about the future level of investment-specific technology. We therefore call η_1^I the IST news shock. Without loss of generality, the investment-specific technology also includes a stationary component ν_t^I, capturing either a measurement error or temporary IST shocks. The shock to this component $\eta_{2,t}^I$ is unanticipated and influences investment-specific technology on impact.

TFP_t^C includes three components. The first is a diffusion process of neutral technology. The second, a stationary component ν_t^N can be interpreted as a temporary shock to TFP_t^C (e.g., technological, policy, or financial shocks). The third component is novel and captures the spillover effects of permanent IST innovations, the magnitude of which is governed by the parameter α.[26] Specifically, given the diffusion process, the value of α captures the elasticity of TFP^C with respect to the IST news shock η_1^I in the long run.[27] In standard real business cycle models (e.g. (Greenwood, Hercowitz and Krusell, 1997) $\alpha = 0$. By contrast, if IST is a general purpose technology, α can

[24] Leeper and Walker (2011) argue that news shocks containing moving-average (MA) components, as in (2.9), are better in line with slow technology diffusion than i.i.d. news shocks drawn from distinct probability distributions.

[25] The assumption that η_1^I is orthogonal to η_1^N is consistent with the empirical findings of BFFK that the correlation between the consumption-sector technology shocks and the relative equipment-investment-consumption technology shocks is close to zero, using BFFK's approach to measure the technology series for each sector.

[26] Note that equation (2.10) implicitly assumes that non-IST permanent shocks to PC, v_{1t}, are orthogonal to consumption-sector TFP. In Appendix 2D, we will relax this assumption and discuss the validity of our results in the presence of permanent shocks to consumption-specific technology, another potential common shock to both the relative price of investment and consumption-sector TFP.

[27] While investment in our model corresponds to total private investment, it is argued that investment-specific technology is embodied in equipment and software. Therefore, our model's IST diffusion process could be a sum of two separate diffusion processes, one spilling over to the rest of the economy and the other not. This would not change the interpretation of α as the importance of embodied technology to the productivity of the rest of the economy.

be sizable. The spillover effect α, in reality, captures not only the technological spillover, but also unmeasured complementary investment in organizational capital (e.g., managerial innovations) or purposeful innovation in R&D accompanied by an introduction of information-communication technology (ICT) capital. For example, Acemoglu, Aghion, Lelarge, Reenen and Zilibotti (2007) show both theoretically and empirically that the diffusion of new technology is important for the firm's decision on decentralization in an imperfect information environment.[28]

We now express TFP in terms of primitive shocks. Plugging equation (2.9) and (2.10) into (2.8), we can rewrite aggregate TFP as

$$\log TFP_t = \sum_{i=0}^{\infty} d_i^N \eta_{1,t-i}^N + \beta \sum_{i=0}^{\infty} d_i^I \eta_{1,t-i}^I + \nu_t, \tag{2.13}$$

where $\beta \equiv \alpha + w^I$ captures the overall effects of IST news shocks on aggregate TFP, and $\nu_t \equiv w^I \nu_t^I + \nu_t^N$ captures the transitory component of aggregate TFP.

Note that this specification nests the process of TFP adopted in Beaudry, and Portier (2006), which assume that there is a single news shock on TFP, driven by innovations in neutral technology, and a single transitory shock.[29]

$$\log TFP_t = \sum_{i=1}^{\infty} d_i \eta_{1,t-i} + \nu_t. \tag{2.14}$$

Such an interpretation of the TFP news shock applies also to the broader literature on news shocks. Absent the direct and the spillover effects of the IST news shock on measured TFP, the news shock to aggregate TFP is equivalent to the news shock to neutral technology. This view, however, may not hold in light of the potential spillover effect of the IST news shock on aggregate TFP fluctuations.

We now explore the contribution of the IST news shock to TFP and PC at different hori-

[28]Also, the assumption that complementary investments are needed to derive the full benefit of ICT is supported by firm-level evidence ((Bresnahan, Brynjolfsson and Hitt, 2002). Basu, Fernald and Oulton (2004) construct a model in which improvement in ICT technology influences aggregate TFP through both spillover and complementary investment in organizational capital.

[29]In Beaudry, and Portier (2006), there is no explicit distinction between neutral and investment-specific technology.

zons. Equation (2.13) implies that the contribution of the IST news shock η_1^I to the fluctuations of aggregate TFP hinges on the magnitude of β, which further depends on its spillover effects α. The larger is the spillover effect, the larger is the contribution of η_1^I to TFP fluctuations. By contrast, under the standard RBC models ($\alpha = 0$), the contribution of η_1^I is arguably small, due to the small share of investment in GDP in the U.S. data. Formally, the contribution of the IST news shock to TFP can be measured by the share of the forecast error variance (FEV) of TFP attributable to the IST news shock η_1^I, k quarters ahead, denoted as $\Omega_{TFP,\eta_{1,t}^I}(k)$.

$$\Omega_{TFP,\eta_1^I}(k) = \frac{\beta^2\sigma^2_{\eta_1^I}\sum_{j=0}^{k-1}(d_j^I)^2}{\Omega_{TFP}(k)}, \tag{2.15}$$

where $\Omega_{TFP}(k)$ denotes the forecast error variance of TFP k-step ahead, which is the sum of the contribution of the three primitive shocks, η_1^I, η_1^N, and η_2^N. Obviously, the magnitude of the contribution of the IST news shock to the FEV of TFP depends on their diffusion speed δ_I and the forecast horizon k. Nonetheless, the larger is $\beta^2\sigma^2_{\eta_1^I}$, the larger is the share of forecast error variance of TFP attributable to η_1^I in all horizons except for the impact period. Intuitively, the contribution of IST news shocks to overall TFP fluctuations depends on both their internal propagation, captured by β, and their magnitude, captured by $\sigma^2_{\eta_1^I}$. Appendix 2C shows that if $k \to \infty$, equation (2.15) becomes

$$\Omega_{TFP,\eta_1^I}(k) = \frac{1}{1+\sigma^2_{\eta_1^N}/\left(\beta^2\sigma^2_{\eta_1^I}\right)}. \tag{2.16}$$

Equation (2.16) shows that, in the long run, the share of the FEV of TFP attributable to the IST news shock depends positively on $\beta^2\sigma^2_{\eta_1^I}/\sigma^2_{\eta_1^N}$, which is the contribution of the IST news shock to the variance of aggregate TFP relative to its counterpart for the permanent neutral technology shock. This is because, as time goes to infinity, the contribution of all transitory shocks to TFP becomes essentially zero.

Similarly, we can derive the FEV of PC attributable to the IST news shock k steps ahead.

Combining equation (2.5) with equation (2.9), we can obtain the inverse of the relative price of investment as follows:

$$\log PC_t = \sum_{i=0}^{\infty} d_i^I \eta_{1,t-i}^I + \nu_t^I + \omega_t + \varpi_t.$$

The share of the FEV of PC attributable to the IST news shock k quarters ahead, which we denote as $\Omega_{PC,\eta_1^I}(k)$, is

$$\Omega_{PC,\eta_1^I}(k) = \frac{\sigma_{\eta_1^I}^2 \sum_{j=0}^{k-1} (d_j^I)^2}{\Omega_{PC}(k)}, \tag{2.17}$$

where $\Omega_{PC}(k)$ denotes the FEV of PC k-step ahead. Appendix 2C shows that as $k \to \infty$, equation (2.17) becomes

$$\Omega_{PC,\eta_1^I}(k) = \frac{1}{1 + \sigma_{\upsilon_1}^2 / \sigma_{\eta_1^I}^2}. \tag{2.18}$$

Equation (2.16) and (2.18) imply that the same structural shock—the IST news shock—would maximize the FEVs of both TFP and PC in the long run only if the spillover effects of the IST news shock is sufficiently large and the IST news shock plays a dominant role in the long-run fluctuations in PC. This suggests a method to quantify the magnitude of the effects of the IST news shock on aggregate TFP, by computing the correlation of the news shocks to TFP and PC identified under the MFEV approach with a sufficiently long forecast horizon.

We now analytically derive the correlation of the two identified news shocks and establish the link between such a correlation and the relative importance of the IST news shock in anticipated future TFP fluctuations. We first establish the mapping in our model between the primitive shocks η and the identified news shocks ε under the MFEV approach. According to our model, the shock maximizing the FEV of PC at $\underline{k} = \overline{k} \to \infty$ (with zero impact effect) simply maps into the sum of IST news shocks and υ_{1t}

$$\tilde{\varepsilon}_t^{PC} = \eta_{1t}^I + \upsilon_{1t}. \tag{2.19}$$

Similarly, by maximizing the FEV of TFP at $k \to \infty$, the identified news shock is

$$\tilde{\varepsilon}_t^{TFP} = \beta \eta_{1t}^I + \eta_{1t}^N. \tag{2.20}$$

That is, the shock that best explains the long-run fluctuations of TFP maps into a linear combination of the permanent innovations to IST and neutral technology.

Note that in our framework, news shocks to the inverse of the relative price of investment (PC) is not identical to IST news shocks. Nonetheless, the importance of IST news shocks for long-run fluctuations in PC can still be verified by examining the share of the FEV of PC attributable to TFP news shocks. Given that the IST news shock is the only common long-run shock underlying the fluctuations in PC and TFP, a large share of FEV of PC attributable to TFP news shocks in the long run, as later shown by our empirical evidence, implies that IST news shocks play the dominant role in the long-run fluctuations in PC.

The correlation coefficient between the two news shocks, identified by maximizing the FEVs of the respective variables at $k \to \infty$ can, therefore, be expressed as follows:

$$\begin{aligned} \rho\left(\tilde{\varepsilon}_t^{PC}, \tilde{\varepsilon}_t^{TFP}\right) &= \frac{cov\left(\tilde{\varepsilon}_t^{PC}, \tilde{\varepsilon}_t^{TFP}\right)}{\sigma_{\tilde{\varepsilon}_t^{PC}} \cdot \sigma_{\tilde{\varepsilon}_t^{TFP}}} \\ &= \frac{\beta \sigma^2_{\eta^I_{1t}}}{\sqrt{\sigma^2_{\eta^N_1} + \beta^2 \sigma^2_{\eta^I_1}} \sqrt{\sigma^2_{\eta^I_1} + \sigma^2_{\upsilon_1}}} \\ &= \frac{1}{\sqrt{1 + \sigma^2_{\eta^N_1} / \left(\beta^2 \sigma^2_{\eta^I_1}\right)} \sqrt{1 + \sigma^2_{\upsilon_1} / \sigma^2_{\eta^I_1}}}. \end{aligned} \tag{2.21}$$

The right-side of equation (2.21) captures the product of the share of the FEVs of TFP and PC attributable to IST news shocks. Intuitively, the correlation of the two news shocks depends on how important the IST news shock is to the long-run fluctuation in both TFP and PC, as captured by $\beta^2 \sigma^2_{\eta^I_1}$ and $\sigma^2_{\eta^I_1}$, relative to other permanent shocks. Hence, a high correlation is achieved *only if* the spillover effect of the IST news shock is sufficiently large and the IST news shock plays a dominant role in the long-run fluctuations in PC, which we can verify separately by examining the share of the FEV of PC explained by the TFP news shocks in the long run. Furthermore, if the IST news shock is an important source of anticipated long-run TFP fluctuations, we should observe that the correlation of the identified news shocks to TFP and PC tend to increase with the forecast horizon chosen under the MFEV approach, an implication that we examine in Section 2.5.3.

In our baseline framework, we assume that the IST news shock is the only common long-run shock to PC and consumption-sector TFP. In practice, however, spillover may originate from innovations in consumption-specific technology to the investment sector, rendering shocks to consumption-specific technology an alternative candidate as the common driving force underlying TFP and PC. Therefore, in Appendix 2.D, we also consider an alternative data-generating process that allows spillover in both directions.[30] We show that the correlation between the news shocks on TFP and PC would be negative if the spillover from the consumption to the investment sector dominates, and vise versa. The intuition is simple: a positive innovation in consumption-specific technology would drive up the relative price of investment, while at the same time increasing aggregate TFP. Therefore, the sign of the correlation of the two identified news shocks sheds light on whether IST news shocks or shocks to consumption-specific technology dominate the underlying common driving force of TFP and PC.

Finally, we must ask how much of the overall contribution of the IST news shock to aggregate TFP fluctuations is due to the spillover effect α, and how much is simply due to the direct effect w^I? Appendix 2E shows that as $k \to \infty$, β equals

$$\beta = \sqrt{\frac{\Omega_{TFP,\eta_1^I}(k) \times \sigma_{TFP}^2}{\Omega_{PC,\eta_1^I}(k) \times \sigma_{PC}^2}}, \tag{2.22}$$

where σ_{TFP}^2 and σ_{PC}^2 denote the variances of news shocks to TFP and PC, respectively. Therefore,

[30]We thank one referee for this suggestion.

with the value of w^I, the investment share in aggregate value-added, obtained from the U.S. data, we can measure the importance of the spillover effect α.

In summary, we provide a model of IST spillover to offer a structural interpretation of the news shocks to PC and TFP, identified under the MFEV approach. Based on the model, we show that the correlation of these two news shocks, identified by maximizing the sum of the FEVs over a sufficiently long horizon, sheds light on the quantitative importance of IST news shocks to anticipated future TFP fluctuations.

Data and Specification Issues

Our empirical exercise uses U.S. data over the period 1961:Q3 to 2008:Q4. The two key series in our VAR exercise are the inverse of the price of investment goods relative to consumption and a measure of total factor productivity. To measure the importance of news shocks to macro variables, we also include consumption, hours worked, output, and investment in our VAR system. Later, we will consider larger VAR systems that also include an index of stock market value (SP), an index of consumer confidence, the federal funds rate, and inflation in the CPI index. In robustness checks, we consider alternative specifications that include a measure of total factor productivity for the consumption sector and term spread. Therefore, we also present the source of this data.

The inverse of the relative price of investment corresponds to the ratio of the chain-weighted deflators for consumption and investment, which is taken from Justiniano, Primiceri and Tambalotti (2011). The denominator is the National Income and Product Accounts (NIPA) deflator for durable consumption and private investment. However, Gordon (2199) and Cummins and Violante (2002) argue that NIPA's quality adjustments may underestimate the rate of technological progress in areas such as equipment and software; an issue that can distort the measured contribution of IST changes to both growth and business cycles. Consequently, Gordon constructed the alternative price series for producer durable equipment, which was later updated by Cummins and Violante (GCV deflator hereafter). For our baseline model, we work with the NIPA deflators; however, we also check the robustness of our results to the use of the GCV deflator.[31]

The series of aggregate TFP growth is taken from Fernald (2012), measured as the growth rate of business-sector TFP.[32] We would like our TFP series to proxy for technological changes. Therefore, the TFP series we adopt are corrected for capital utilization. Our main findings below are robust to the choice of TFP series unadjusted for capital utilization.

We construct the growth rate of TFP in the consumption sector according to

$$\Delta \log TFP_t^C = \Delta \log TFP_t - w^I \Delta \log P_t^C / P_t^I, \tag{2.23}$$

with the data series for w^I taken from Fernald (2012).[33] We back-out the log levels of both aggregate and consumption-sector TFP with initial levels normalized to zero.

The consumption measure C is the per capita value of the real personal consumption of nondurable goods and services. Investment measure I is the per capita value of the sum of real personal consumption of durable goods and real fixed private domestic investment. Hours H is per capita hours worked in the nonfarm business sector.[34] Output Y is GDP per capita. We use the corresponding chain-weighted deflators to obtain the real series. All per capita series are obtained by dividing the corresponding aggregate variables by the civilian non-institutional population aged 16 and above, obtained from the Bureau of Labor Statistics.

The measure of stock prices is the per capita real S&P 500 index. The S&P 500 composite index is taken from Robert Shiller's webpage. The price deflator is the price index for gross value

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[31] We thank Patrick Higgins from the Federal Bank of Atlanta for sharing the updated series of GCV deflators.

[32] The data is updated on John Fernald's webpage http://www.frbsf.org/economic-research/economists/john-fernald/.

[33] Note that equation (2.23) implicitly assumes that $\Delta \log \Phi_t = \Delta \log P_t^C / P_t^I$; that is, the wedge between IST and the inverse of the relative price of investment is time invariant.

[34] The hours data are taken from Valerie Ramey's webpage http://econweb.ucsd.edu/˜vramey/research.html#data.

added in the non-farm business sector, taken from the Bureau of Economic Analysis (Table 1.3.4). The stock index is converted to a quarterly frequency by taking the average of the monthly stock index over each quarter. The data for the consumer confidence index, federal funds rate, and CPI index are from Beaudry, Nam and Wang (2011). The data for the term spread is the difference between the 60-month Fama-Bliss unsmoothed zero-coupon yield from the CRSP government bonds files and the Federal Funds rate, taken from Kurmann and Otrok (2013).

We estimate vector auto-regressions (VARs) in levels of all variables in the baseline specification. We prefer the level specification because, while several of these series appear to be $I(1)$, estimating the system in levels will produce consistent estimates of impulse responses and is robust to the cointegration of unknown forms.[35] In Section 5.2.4, however, we show that our results are very similar when we estimate a vector error correction model (VECM). According to standard likelihood methods, four or five appears to be the optimal lag order when testing in an ascendant way for the optimal number of lags from two quarters up to three years. We therefore choose to work with four lags in our baseline model; however, all the results are robust to adopting a five-lag specification. We compute the error band with residual-based bootstrap, as in Kilian (1998).

In comparison with the results in the literature, we let the lower bound of the forecast horizon $\underline{k}$ in equation (2.1) be zero. We set the upper bound of the forecast horizon under the MFEV approach to $\overline{k} = 120$ quarters. Our choice of a large upper bound is motivated by the fact that, in reality, technology adoption typically takes a long time. For example, Jovanovic and Lach (1997) report that, for a group of twenty one innovations, it takes fifteen year for its diffusion to go from 10 percent to 90 percent (the 10-90 lag). In addition, Grubler (1991) finds that, among a group of 265 innovations, the 10-90 lag is between 15 and 30 years for most diffusion processes. Therefore, our choice of the upper bound of the forecast horizon is consistent with the upper bound

[35] Moreover, according to Fisher (2010), invalid assumptions concerning common trends may produce misleading results.

of the diffusion lag of a new technology. In Section 5.3, we will vary the upper bound of the forecast horizon to equal 40, 60, and 80 in order to explore how the correlation of the two identified news shocks and their impact on macro variables change under different values of the upper bound. We also consider an alternative MFEV approach, under which we equalize the lower and upper bound of the forecast horizon, i.e., $\underline{k} = \overline{k} = k$.

Results

In this section, we first report the results under the baseline specification. Then we check the robustness of our main findings to alternative measures of investment deflators, alternative TFP series, different lags, and alternative specifications. Finally, we explore the correlation of news shocks to TFP and PC identified under the alternative forecast horizons.

Baseline Estimates

This subsection presents the main results of the paper. We first report the results under a six-variable system. We then extend our results to larger systems with additional forward-looking and nominal variables.

A Six-variable System

Figure 2.1 displays the IRFs of various variables to the news shock to PC (solid line), with 16 to 84 percent posterior coverage intervals shaded in gray. To compare, we also plot their counterparts to news shocks to TFP (dashed line). What is striking is that the IRFs of all the variables to the two news shocks are surprisingly close to each other. Specifically, under both news shocks, the response of PC—the inverse of the relative price of investment—is essentially zero on impact. After that, PC gradually increases, and then peaks at 25 quarters at 0.7 percent higher than its pre-shock value. In regards to TFP, we see that the initial response of TFP to both shocks is negative within the first ten quarters. After that, TFP steadily increases. In the long run, the news shock to PC seems to have a permanent positive effect on TFP. Such a pattern is puzzling from the viewpoint of the standard real business cycle theory, but is consistent with the response of TFP to the IST news shock as implied by equation (2.13). In particular, the insignificant reaction of TFP on impact and its gradual increase to a permanently higher level suggests that the news shock to PC captures a slow diffusion process of general purpose technology that is anticipated by economic actors.[36] Furthermore, the positive comovement of PC and TFP in response to the news shock to PC is consistent with the spillover from IST news shocks to consumption-sector TFP, rather than from the opposite direction.

Consider now the macro variables. We see that the IRFs of all macro variables to these two news shocks are hump-shaped and peak at six quarters, before TFP starts to rise above zero.[37] Moreover, consumption significantly increases on impact. This suggests that consumer confidence or sentiment, triggered by expected future TFP fluctuations, plays some role in the transmission of news shocks into consumption in initial periods.[38] Such a transmission mechanism is potentially important for technological innovations, which typically have a long diffusion lag, in driving business cycle fluctuations.

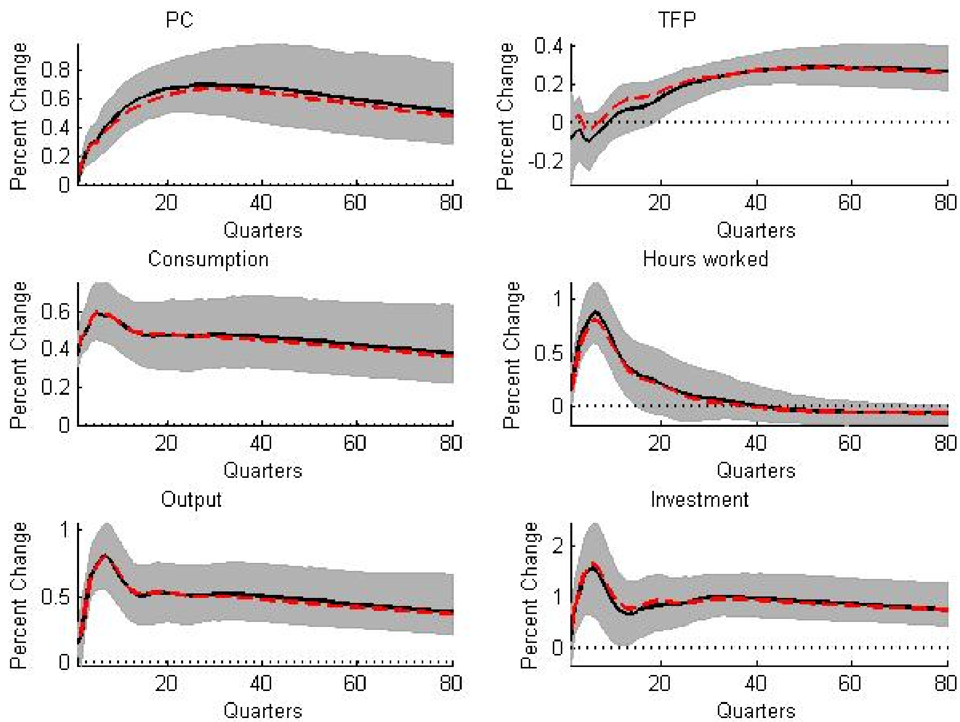
Also of note is that the impact responses of all macro variables to both news shocks are positive. This is different from the findings of Barsky and Sims (2011), in which news shocks to TFP have a negative impact effect on hours worked, GDP, and investment. Intuitively, an IST

[36]The initial negative response of aggregate TFP to news shocks to PC is consistent with the findings of Basu, Fernald and Oulton (2004) using industry-level data. They find that controlling for past ICT growth, industry TFP growth in the U.S. appears negatively correlated with increases in ICT usage in the late 1990s. They argue that this is because, contemporaneously, investments in ICT may be associated with lower TFP as resources are diverted to reorganization and learning.

[37]Specifically, consumption peaks at 5 quarters, investment and hours at 6 quarters and output at 7 quarters.

[38]We will later show than the measured consumer confidence responds positively to our identified news shocks.

Figure 2.1: Impulse Responses to News Shocks to PC and TFP—Baseline Specification.



Notes: IRFs to the news shock to PC (solid black line) and TFP news shock (dashed red line) in the six-variable system with the range of forecast horizons $0 \leq k \leq 120$. The shaded gray area represents the 16-percent and 84-percent quantiles of the empirical distribution of the IRFs in the identification of the news shock to PC. The distribution is the bootstrapped impulse responses obtained through the residual-based resampling with 1,000 replications.

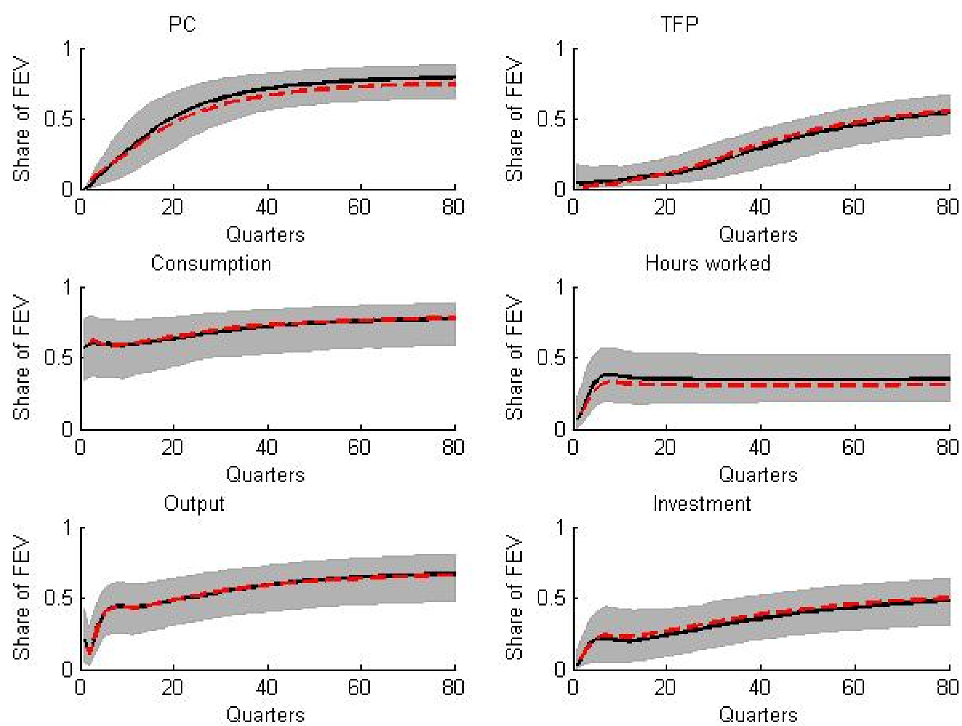
news shock would not only increase the demand for current investment in the presence of capital adjustment cost, but would also trigger an increase in consumption demand via the anticipated increase in aggregate TFP. Moreover, in the long run, apart from the variable hours worked, which converges to the initial level after the peak, all other variables converge to a new long-run level. This is consistent with our model's prediction that the news shocks to embodied technology have permanent effects.

The similarity of the two news shocks is further confirmed by the inspection of the forecast error variance decomposition shown in Figure 2.2. We see that the shares of the FEVs of both PC and TFP attributable to these two news shocks are quantitatively similar. Specifically, on impact, both news shocks explain little variation in PC. Over time, however, the FEV of PC attributable to the news shock to either PC or TFP increases monotonically. In particular, the news shock to TFP alone contributes to more than 70 percent of the fluctuations in PC 80 quarters ahead, a result that is, again, puzzling from the perspective of the standard business cycle model. Such an observation, however, is consistent with the view that IST news shocks, which spill over to consumption-sector TFP, play a dominant role in the long-run fluctuations in PC. Meanwhile, despite explaining only a small fraction of the FEV of TFP at horizons of 16 quarters or less, both shocks can account for more than 50 percent of TFP fluctuations for forecast horizons beyond 80 quarters. This suggests a slow diffusion and spillover process of IST innovations.[39]

Turning to the macro variables, news shocks can account for about 60 percent of the FEV of consumption at business cycle frequencies. More importantly, both news shocks are important for hours and output fluctuations at business cycle frequencies, explaining about 40 percent of their FEVs eight quarters ahead. Interestingly, this finding is in line with the results in Fisher (2006),

[39]The slow diffusion process of news shocks to PC to aggregate TFP is also implied by Ben-Zeev and Khan (2013, Figure 1 and 2). Following strictly their identification strategy, we find that, although the share of FEV of TFP attributable to news shocks to PC is only 0.07 20 quarters ahead, it significantly increases to 0.4741 80 quarters ahead.

Figure 2.2: Share of the FEV Decomposition Attributable to News Shocks to PC and TFP in the Baseline Specification.



Note: Forecast error variances (FEVs) to the news shock to PC (solid black line) and the TFP news shock (dashed red line) in the six-variable system with the range of forecast horizons $0 \leq k \leq 120$. The shaded gray area represents the 16-percent and 84-percent quantiles of the empirical distribution of the FEVs in the identification of the news shock to PC. The distribution is the bootstrapped FEVs obtained through the residual-based resampling with 1,000 replications.

which identifies under long-run restrictions investment-specific shocks and finds they explain 40-60 percent of the short-run variations in hours and output.[40] By contrast, the fluctuation of investment attributable to the news shocks to TFP or PC increases steadily in forecast horizons. This suggests that, over business cycles, other shocks—such as financial shocks—might play an important role in investment fluctuations. Over the long run, however, technical improvements start to play an important role in investment variations. Table 2.1 summarizes the FEV coefficients of various variables attributable to the news shock on PC at different time horizons.

Figure 2.3 plots the time series of the identified news shock to TFP and PC, with the shaded areas representing NBER-dated recession periods. As we can see, both shocks are procyclical and track each other fairly closely. Moreover, the magnitudes of the volatility of both shocks are very similar. The correlation of these two shocks is as high as 0.9773. This quasi-identity of the two identified news shocks provides further support that IST news shocks are the main primitive shocks underlying the long-run variations of both aggregate TFP and the relative price of investment.

Table 2.1: The Share of the FEVs Attributable to the News Shock to PC in the Baseline Specification.

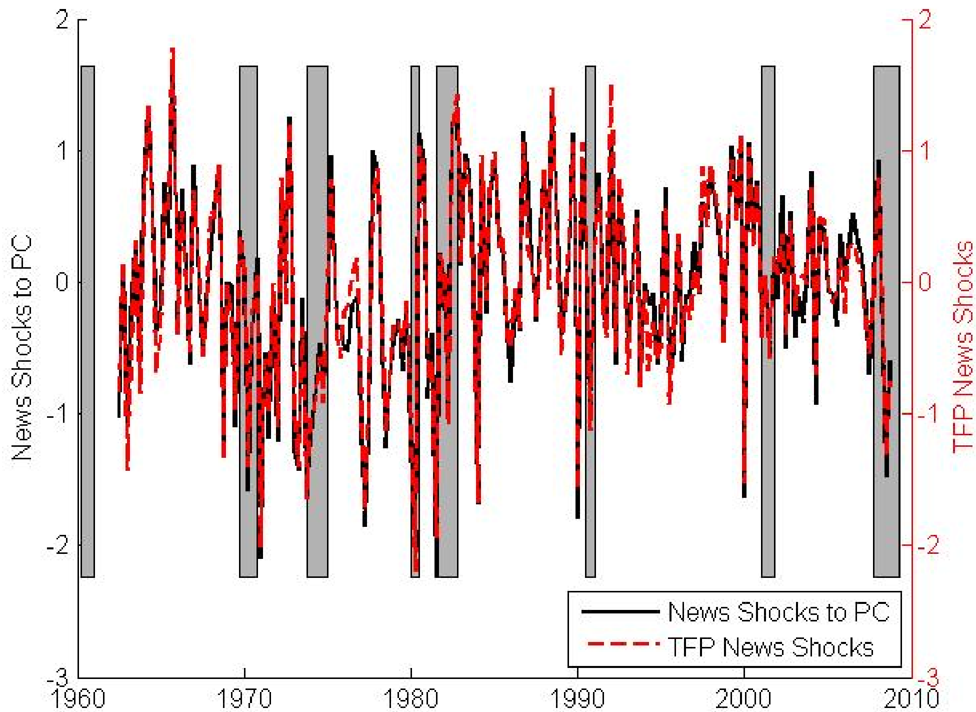
	$k=0$	$k=4$	$k=8$	$k=16$	$k=40$	$k=80$
PC	0.000	0.0865	0.2005	0.4219	0.7088	0.7859
TFP	0.036	0.0455	0.0562	0.0858	0.2846	0.5314
Consumption	0.5768	0.5962	0.5792	0.6144	0.7195	0.7808
Hours	0.0675	0.2912	0.386	0.3509	0.3387	0.3477
GDP	0.1992	0.3166	0.4344	0.4481	0.5855	0.6708
Investment	0.0248	0.1835	0.2073	0.2152	0.3478	0.4721

Note: The coefficients are obtained from computing the FEVs in the six-variable system with the forecast horizon $0 \leq k \leq 120$. The letter k denotes the forecast horizon. The number denotes the fraction of the total forecast error variance of each variable attributable to the identified news shock to PC.

We now quantify the relative importance of the spillover effect of the IST news shock. Our

[40] In Section 2.5.2, we show that our main findings are robust to dropping zero restrictions, suggesting that long-run shocks to PC are largely anticipated.

Figure 2.3: Time Series of the Identified News Shocks to PC and TFP and U.S. Recessions.



Note: The time series of the news shock to PC and TFP news shock are obtained from the six-variable system with the range of forecast horizons $0 \leq k \leq 120$. The shaded areas represent periods of recessions as dated by NBER.

empirical findings suggest that IST news shocks dominate the long-run fluctuations of PC. Accordingly, we can proxy $\Omega_{TFP,\eta_1^I}(k)$ and $\Omega_{PC,\eta_1^I}(k)$ by the shares of FEV of TFP and PC attributable to the identified news shocks to PC. Since equations (2.16) and (2.18) only hold asymptotically, we choose a sufficiently long horizon, $k = 120$, to compute $\Omega_{TFP,\eta_1^I}(k)$ and $\Omega_{PC,\eta_1^I}(k)$. Then, with the estimated variances of the news shocks to TFP and PC, equation (2.22) gives $\beta = 0.89$.[41] According to Fernald (2012), the value of the investment share in business output is, on average, $w^I = 0.21$ during our sample period. This gives the value of α, the measure of IST spillover effects, as $\alpha = \beta - w^I = 0.68$. Comparing the value of α with w^I, we conclude that the spillover effect plays the key role in the transmission of the IST news shock to anticipated TFP fluctuations.

Large VAR Systems

We next identify the two news shocks in larger VAR systems. We first sequentially add a measure of stock prices and consumer confidence into the baseline VAR specification. It has been argued that both stock prices and consumer confidence are forward-looking. Therefore, including these additional variables in the system will help to identify the news shocks.

Figure 2.4 reports the IRFs in the system with stock prices. Again, for all variables, the IRFs to the two news shocks are very close to each other and similar to their counterparts in the baseline VAR system. The correlation coefficient, as reported in Table 2.2, is 0.9376. Interestingly, stock prices respond positively to both news shocks, despite a fall in the relative price of investment (i.e., an increase in PC). A negative comovement of stock prices and the relative price of investment is difficult to obtain in a standard business-cycle model with either IST shocks or neutral technology shocks. This is because a positive neutral technology shock would drive up both the stock prices and the relative price of investment, as it increases the demand for investment goods; while a positive

[41] Specifically, the FEVs of TFP and PC attributable to the news shock to PC at the horizon of 120 quarter are 0.7542 and 0.8911, respectively; and the variances of the news shocks to PC and TFP are 0.5920 and 0.5545, respectively.

IST shock would drive down both the stock price and the relative price of investment, as it increases the supply of investment goods.[42] However, the joint observation of procyclical stock prices and the countercyclical relative price of investment is in line with a business-cycle model of IST spillover, in which the permanent IST innovations are the single major technological source. Intuitively, a positive IST innovation leads to a fall in the relative price of investment via an increase in the supply of investment goods, whereas its impact on anticipated future productivity tends to boost aggregate consumption and, therefore, the demand for installed capital and stock prices.

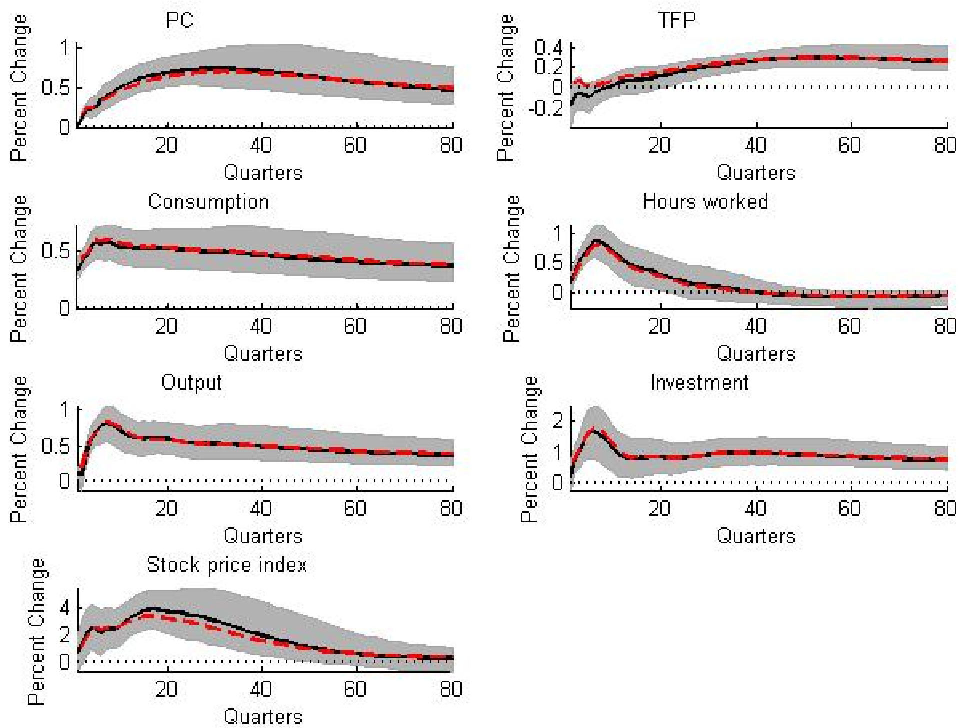
The addition of consumer confidence to our VAR renders a very similar outcome. The correlation coefficient of the two news shocks is 0.9498 and consumer confidence rises on impact. This suggests that consumer sentiment may be grounded, at least in part, in anticipated changes in fundamentals.

We then add into our baseline VAR system two nominal variables: the federal funds rate and the inflation rate measured by the percentage change in the CPI index. Figure 2.5 reports the IRFs to the two news shocks. We see that, again, our main findings hold with the addition of nominal variables. The correlation of the two news shocks is 0.9808. Moreover, the inflation rate drops on impact, suggesting that our identified news shocks capture a supply shock.

To summarize, our findings about the high correlation of the two identified news shocks suggest that IST news shocks are important drivers of U.S. business cycles and anticipated future TFP fluctuations. This finding is robust to the addition of other forward-looking and nominal variables.

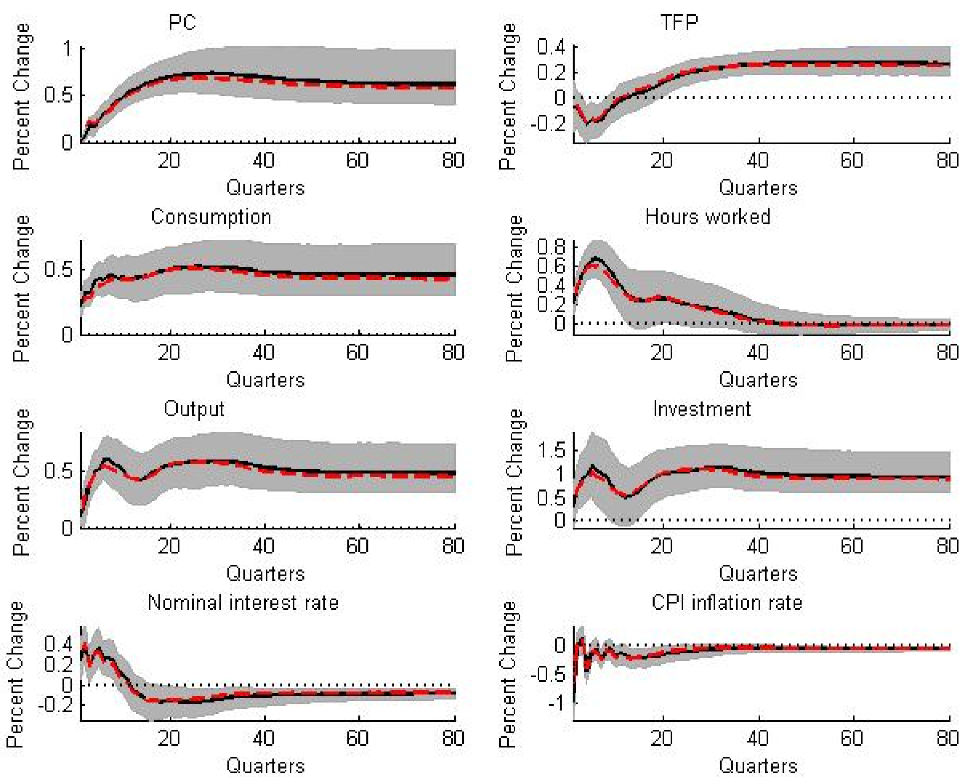
[42] Christiano and Fisher (2003) obtain this negative comovement in a model with capital adjustment cost, when both a permanent investment-specific shocks and a transitory neutral technology shock are present and positively correlated. This is because a positive neutral technology shock drives up the demand for investment goods and, thus, the stock price, while a positive investment-specific shock represents a positive supply shock to investment goods and, thus, drives down the relative price of investment.

Figure 2.4: Impulse Responses to News Shocks to PC and TFP in the Larger System with Stock Prices



Note: Impulse responses to the news shock to PC (solid black line) and the TFP news shock (dashed red line) in the seven-variable system with the range of forecast horizons $0 \leq k \leq 120$. The shaded gray area represents the 16-percent and 84-percent quantiles of the empirical distribution of the impulse response functions in the identification of the news shock to PC. The distribution is the bootstrapped impulse responses obtained through the residual-based resampling with 1,000 replications.

Figure 2.5: Impulse Responses to News Shocks to PC and TFP—larger System with Nominal Variables.



Notes: IRFs to the news shock to PC (solid black line) and the TFP news shock (dashed red line) in the eight-variable system with the range of forecast horizons $0 \leq k \leq 120$. The shaded gray area represents the 16-percent and 84-percent quantiles of the empirical distribution of the impulse response functions in the identification of the news shock to PC. The distribution is the bootstrapped impulse responses obtained through the residual-based resampling with 1,000 replications.

Table 2.2: The Correlation Coefficients of the New Shocks to TFP and PC in Larger VAR Systems

Additional Variable	Correlation Coefficient
Stock Price	0.9376
Consumer Confidence	0.9498
CPI Inflation & FFR	0.9808

Note: The coefficient represents the correlation between the identified news shock to PC and the TFP news shock in the larger systems with $0 \leq k \leq 120$. The left column refers to the additional variables added into the baseline specification.

Robustness Check

In this section, we conduct several robustness checks of our main findings. We first replace the aggregate TFP series with the TFP series in the consumption sector. We also use the GCV quality-adjusted investment deflator. Moreover, we check the robustness of our results under different lags, VAR specifications, and zero restrictions. The correlation coefficients of the two news shocks under these various robustness checks are summarized in Table 2.3. After that, we conduct robustness check of our results under the VECM. Finally, to check whether our identified news shock to PC capture other structural shocks, we provide a cross-correlation of our identified news shock to PC with other macroeconomic shocks identified independently by the literature.

TFP of the Consumption Sector

According to our theory, the high correlation between the two identified news shocks is due to the spillover of embodied technological changes (in particular, equipment and software) to the consumption sector and, thus, the whole economy. Note that equations (2.16) and (2.21) would still hold if we replace aggregate TFP with TFP in the consumption sector, except that β is replaced by α. Therefore, as an alternative method to test our theory, we substitute TFP of the consumption sector for aggregate TFP in the baseline VAR system and explore the IRF of TFP in the consumption sector to the news shock to PC. If the IST spillover effect is quantitatively large, we should observe a similar IRF of TFP in the consumption sector to that of aggregate TFP. By contrast, in the standard business-cycle theory, TFP in consumption sector is orthogonal to IST news shocks.

Figure 2.6 reports the IRFs of various variables to these two news shocks with a TFP series of the consumption sector.[43] Again, we see that the IRFs of all variables to these two news shocks are very similar. In particular, TFP of the consumption sector exhibits a similar IRF to the aggregate TFP shown in Figure 1. The correlation coefficient between these two news shocks is 0.9807. This finding supports the spillover effect of IST as a general purpose technology in aggregate TFP fluctuations.

Alternative Measures of the Price of Investment

We check the robustness of our results with the real price of investment measured by the GCV deflator instead of the NIPA deflator. As is clear in Figure 2.7, the IRFs of all variables to the two news shocks are very close to their counterparts in our baseline system. Hours worked, GDP, and investment all increase on impact. The correlation coefficient of the two identified news shocks is 0.9498.[44]

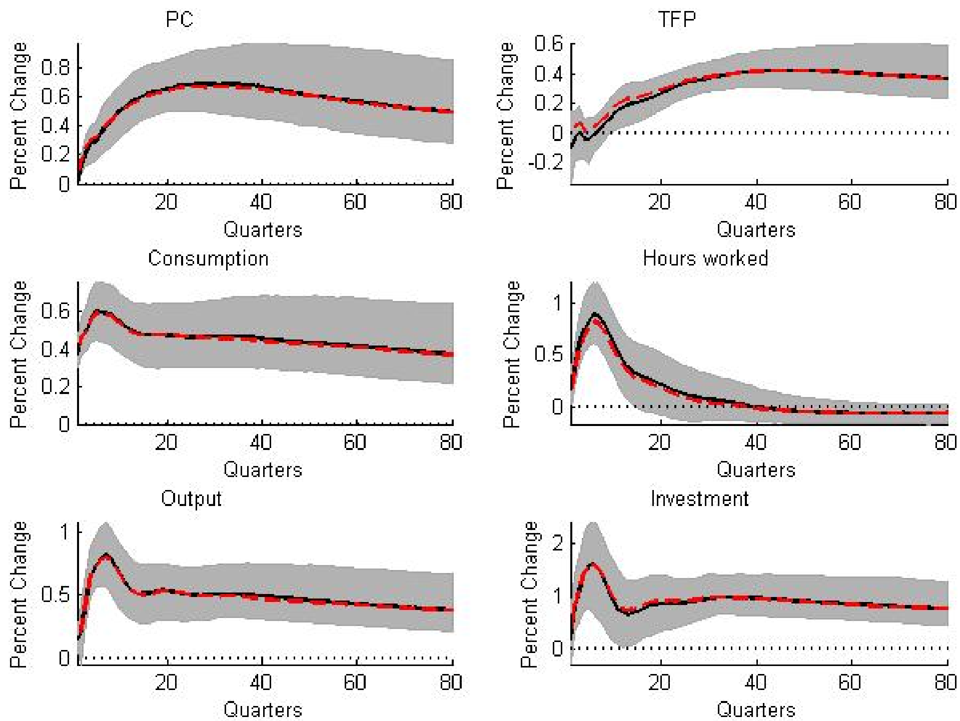
With Different Lags and Specifications

Our results are robust to different lags and alternative VAR specifications. Using five lags in the six-variable VAR system, we obtain a correlation coefficient of the two shocks of 0.9436. Also, similar to that adopted by Kurmann and Otrok (2013), we obtain a correlation coefficient of 0.9283 between the two identified news shocks in a VAR specification that includes the federal fund rate,

[43] Here, the data for TFP of the consumption sector are constructed using the investment deflator from NIPA. Our results are robust when the data series of TFP for the consumption sector is constructed using the GCV investment deflator.

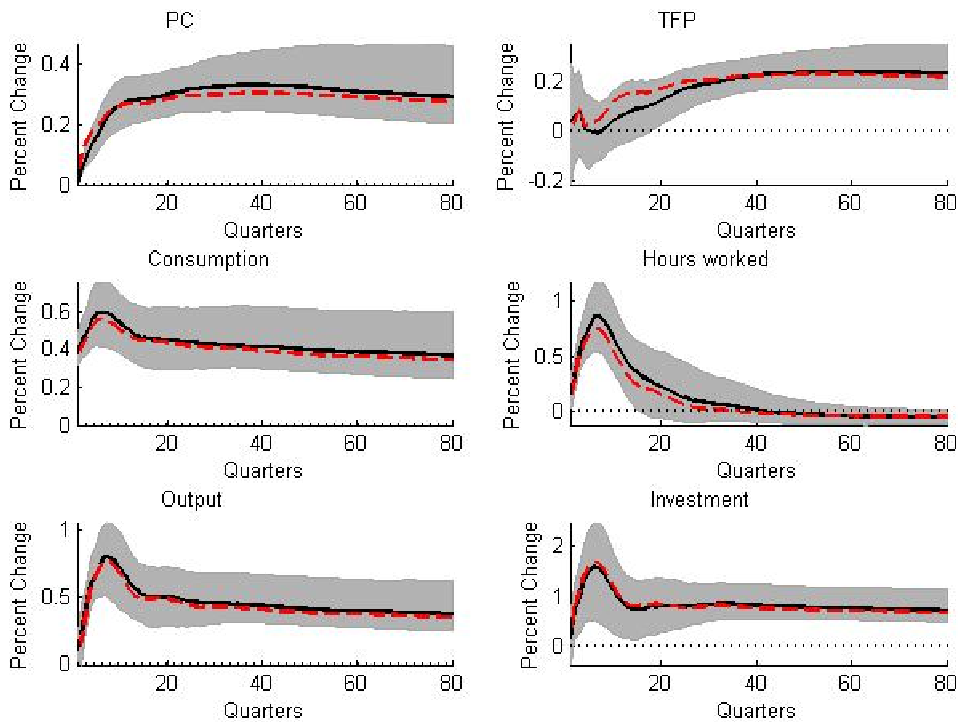
[44] We also adopt the GCV deflator for equipment and software in our robustness check. The correlation between identified news shocks to PC and TFP is, again, very high at 0.885.

Figure 2.6: Impulse Responses to News Shocks to PC and TFP in the System—Consumption-sector TFP



Notes: IRFs to the news shock to PC (solid black line) and TFP news shock (dashed red line) in the six-variable system with the range of forecast horizons $0 \leq k \leq 120$. The shaded gray area represents the 16-percent and 84-percent quantiles of the empirical distribution of the impulse response functions in the identification of the news shock to PC. The distribution is the bootstrapped impulse responses obtained through the residual-based resampling with 1,000 replications.

Figure 2.7: Impulse Responses to News Shocks to PC and TFP in the System—GCV deflator



Notes: IRFs to the news shock to PC (solid black line) and TFP news shock (dashed red line) in the six-variable system with the range of forecast horizons $0 \leq k \leq 120$. The shaded gray area represents the 16-percent and 84-percent quantiles of the empirical distribution of the impulse response functions in the identification of the news shock to PC. The distribution is the bootstrapped impulse responses obtained through the residual-based resampling with 1,000 replications.

Table 2.3: Robustness Checks of the Correlation Coefficients of the New Shocks to TFP and PC

Scenarios	Correlation Coefficient
GCV Deflator	0.9498
Consumption TFP	0.9807
Five Lags	0.9436
Term Spread	0.9283
No Zero Restriction	0.9879

Note: "GCV Deflator" refers to the robustness check in which we replace NIPA investment deflator with the GCV Deflator. "Term Spread" refers to the robustness check in which we adopt the VAR system as in Otrok and Kurmann (2013). "Consumption TFP" refers to the robustness check in which aggregate TFP is replaced with the TFP of the consumption sector. "Five Lags" refers to the robustness check in which we adopt five lags in a six-variable VAR. "No Zero Restriction" refers to the robustness check in which we drop the zero impact restriction when identifying news shocks with the MFEV approach.

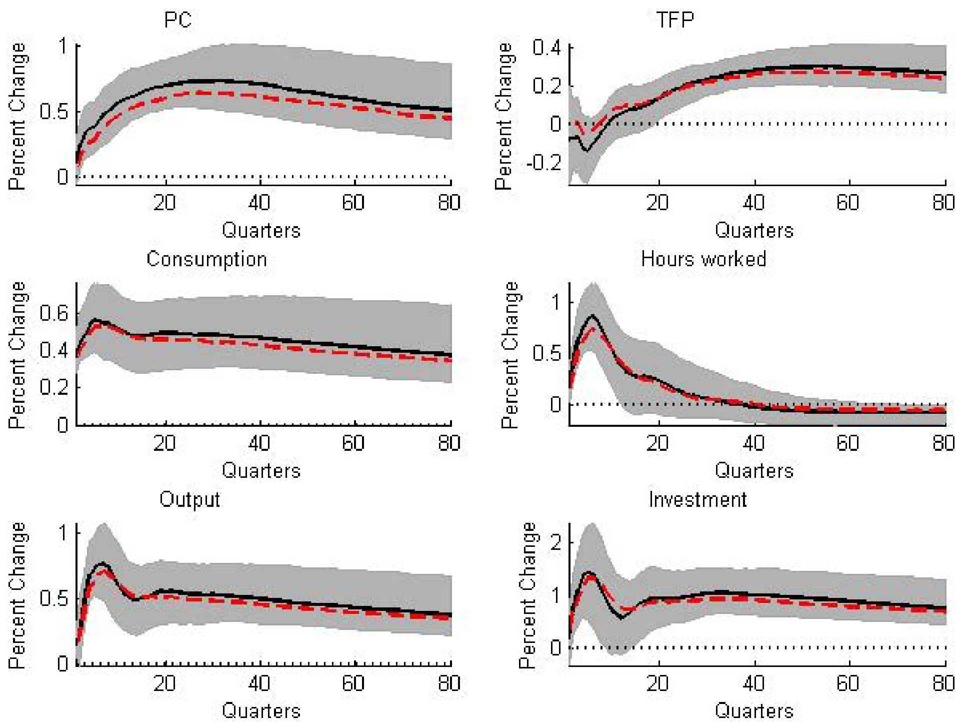
the term spread, and other nominal variables.

Without Zero Restrictions

In our theoretical model, IST news shocks are assumed to have permanent effects on the level of IST and TFP. The natural question is to what extent are the permanent IST innovations in reality anticipated? To this end, we drop the zero restrictions when identifying the shocks that maximize the sum of the FEVs of TFP and PC over a range of a sufficiently long horizon. These shocks are referred to as the long-run shocks to TFP and PC, respectively, and may contain both the anticipated and unanticipated innovations.

Figure 2.8 shows that even without the zero restriction, the impulse responses of all the variables to the two long-run shocks closely resemble their counterparts in the baseline specification (Figure 2.1). In particular, the impact responses of PC and TFP to both long-run shocks are close to zero. The correlation coefficient between the two long-run shocks is 0.9878, again suggesting a common shock underlying the long-run fluctuations of both TFP and PC. Moreover, the correlation between the long-run shock to PC and the news shock to PC identified in the baseline system is

Figure 2.8: Impulse Responses to News Shocks to PC and TFP Identified Without Zero Restrictions



Notes: Impulse responses to the shock to PC (solid black line) and TFP shock (dashed red line) in the six-variable system with the range of forecast horizons $0 \leq k \leq 120$. The shaded gray area represents the 16-percent and 84-percent quantiles of the empirical distribution of the impulse response functions in the identification of the shock to PC. The distribution is the bootstrapped impulse responses obtained through the residual-based resampling with 1,000 replications.

0.9795. This suggests that permanent innovations to investment-specific technology are indeed largely anticipated and are one of the main sources of anticipated TFP fluctuations in the long run.

Alternative Specification: A VECM

We now check the robustness of our results when we estimate a vector error correction model (VECM). We consider a standard VECM for our baseline model (PC, TFP, C, H, Y, and I).[45] It is well-known that cointegration test results vary greatly in terms of the number of co-integrating relations and are also known to have small power. Therefore, we impose one, two, and three common trends in the estimation of the VECM.[46] We recover the associated vector autoregression using the estimated coefficients obtained from the VECM. Then, we identify the relevant news shock—a news shock to PC or TFP—as the innovation that accounts for the sum of the FEVs of the level of PC or TFP over a horizon of $k \in [0, 120]$, but one that has no contemporaneous effect on PC or TFP.

The results are summarized in Table 2.4. As the table indicates, the two identified news shocks under the VECM remain highly correlated for various cointegrating relationships. Moreover, the identified news shock to PC still accounts for a substantial fraction of the forecast error variance of TFP in the long-run. Therefore, we argue that our results about the high correlation of the two empirically-identified news shocks are robust to VECM specifications.

Sub-periods

Both Fisher (2006) and Justiniano, Primiceri and Tambalotti (2011) document a structural break in the relative price of investment: the price has been falling since the early 1950s and exhibits

[45] We follow Lutkepohl (2199) to incorporate stationary variables, such as hours worked, in the model.

[46] Similar to the findings of Schmitt-Grohé and Uribe (2012), we find that a Johansen's trace test for cointegration between TFP and the relative price of investment rejects the null hypothesis of zero cointegrating vectors at high confidence levels when no deterministic trend is included in the system (p-value of 0.00) and when a deterministic trend is included (p-value of 0.02).

Table 2.4: Results from the Estimation of a VECM

Number of Cointegrating Relationships	Correlation Coefficient	Share of FEV of TFP attributable to the News Shock to PC at the horizon $k = 80$
1	0.9700	0.4000
2	0.9005	0.4379
3	0.9327	0.5032

Note: The results are from the estimation of our baseline model, which consists of the relative price of investment (PC), TFP, consumption, hours worked, output, and investment. To incorporate stationary variables, such as hours worked, we follow recommendations from Lutkepohl (2005, pp. 250). After estimating the VECM, the news shock to PC and the TFP news shock are identified under the MFEV of the corresponding variable in levels with the range of forecast horizons as $0 \leq k \leq 120$.

an abrupt increase in its average rate of decline in 1982. Therefore, we split our sample into two sub-samples: 1961:Q3 to 1981:Q4 and 1982:Q1 to 2008:Q4. Since VAR estimates in levels are asymptotically consistent, a shorter sample period increases the standard error of our estimation. However, our focus is on the relative magnitude of the correlation of the two news shocks over these two sample periods. We would expect that the correlation of our news shocks is higher in the second sub-period, as various empirical studies have documented an acceleration of productivity growth of ICT-using industries in the late 1990s and 2000.

Our results confirm our conjecture. In the second sub-sample, the correlation of the two news shocks is 0.9056, while in the first sub-sample it is 0.8105. This implies that the diffusion and spillover of IST innovations as general purpose technology underlies the high correlation of the two identified news shocks.

To summarize, our main findings about the quasi-identity of news shocks to PC and TFP are robust to alternative measures of investment deflators, alternative TFP series, different lags and VAR specifications, and sub-sample data.

Correlation with Other Structural Shocks

It is important to check whether our identified news shocks capture the impact of other prominent macroeconomic shocks. To address this concern, we compute the correlation between our identified news shocks and up to four lags and leads of other important macroeconomic shocks identified separately from the literature. These shocks include the Romer and Romer (2004) monetary policy shock measure, the Romer and Romer (2010) tax shock measure, the Gilchrist and Zakrajšek (2012) credit supply shock measure, and the Kilian (2008) oil supply shock measure.[47]

The results are presented in Figure 2.9 where the correlation between the news shocks to PC and up to four lags and leads of each of the other four shocks are shown, along with the corresponding 95% confidence interval. The results indicate that the cross-correlations are small and insignificant, with the maximum correlation of 0.18 (monetary supply shocks).[48] Thus, we argue that the main results of the paper are not explained by these other macroeconomic shocks.

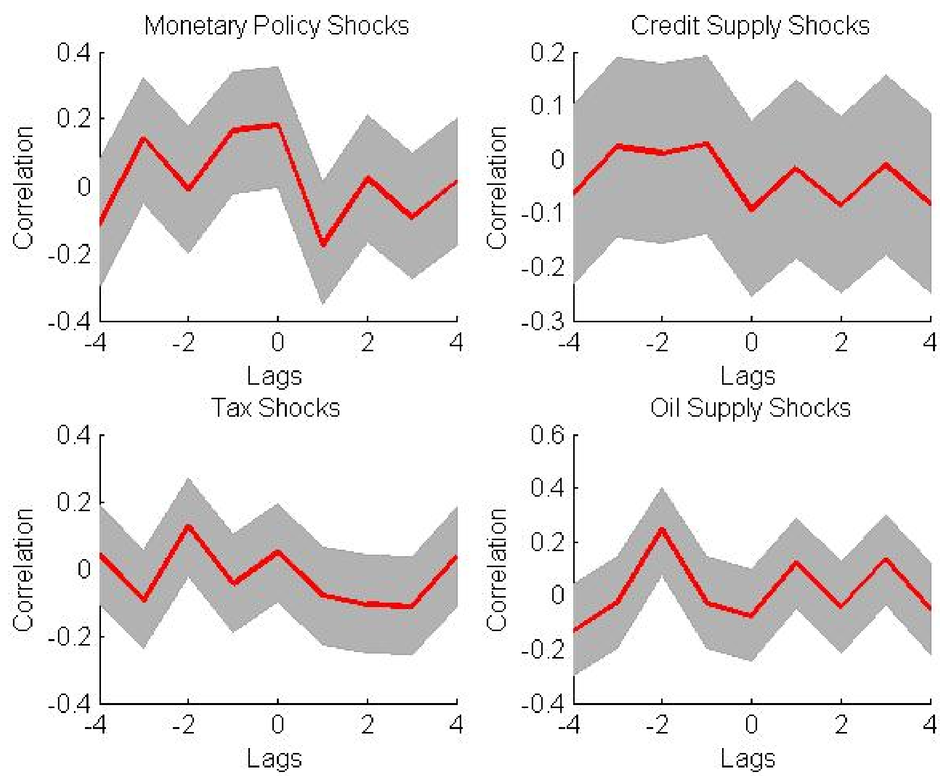
Alternative Forecast Horizons

So far, our news shocks are identified by maximizing the FEVs of the corresponding variables over the forecast horizon $0 \leq k \leq 120$. Apart from the empirical IST diffusion speed, the choice of such a forecast horizon is motivated by our model's implication that the correlation of the two news shocks measures the importance of IST shocks as general purpose technology only if the two news shocks capture the long-run fluctuations of TFP and PC. Another implication of IST diffusion processes is that, given that either TFP or PC may be affected by temporary disturbances in

[47]The data for monetary policy shocks, tax shocks, and oil supply shocks are the corresponding measured shocks constructed by the original papers. For credit supply shocks, we use the shocks to the excess bond premium identified from the VAR exercise in Gilchrist and Zakrajšek (2012). Our result is robust when using the original excess bond premium, constructed as the residual between the actual and fitted value of Gilchrist and Zakrajšek's credit spread.

[48]The p-values for the contemporaneous correlation coefficients of our identified news shocks to PC and all other macroeconomic shocks cannot reject the hypothesis of zero correlation.

Figure 2.9: Cross-correlation between the News Shocks to PC and Leads/Lags of Other Macroeconomic Shocks



Notes: The data for monetary policy shocks are taken from Romer and Romer (2004). The data for credit supply shocks are the shocks to the excess bond premium identified from the VAR exercise in Gilchrist and ZaKrajšek (2012). The data for tax shocks are taken from Romer and Romer (2010). The data for oil supply shocks are from Kilian (2008). The shaded gray area represents the 95% confidence interval.

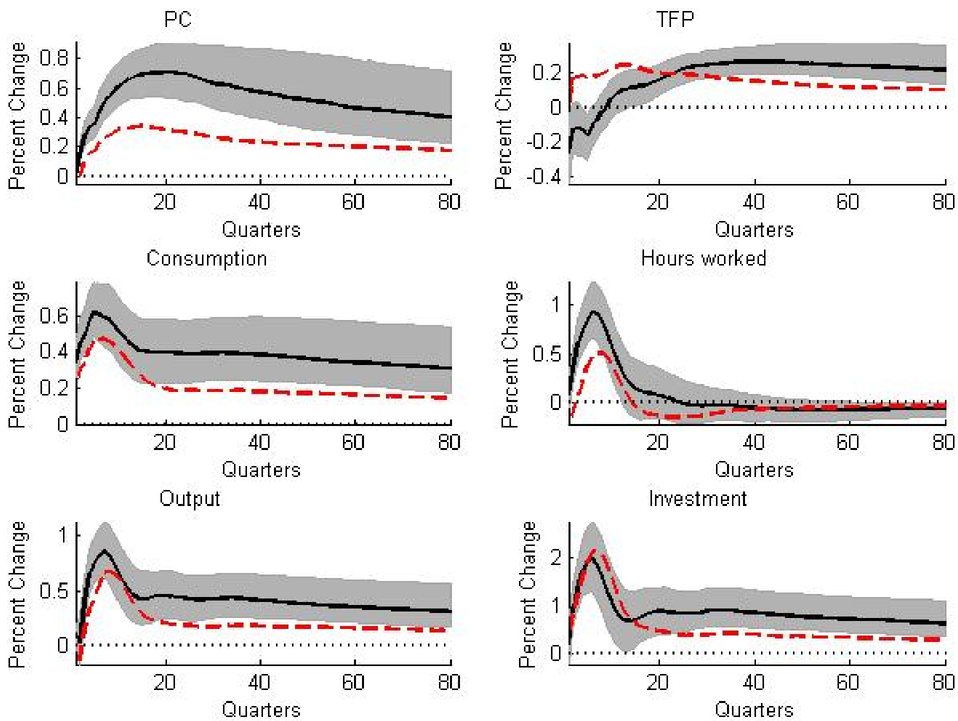
reality, especially in the short run, the correlation of the identified news shocks to TFP and PC tends to increase with the forecast horizon chosen under the MFEV approach. Therefore, as a further test of our theory, we now explore how the correlation of the two identified news shocks varies with the forecast horizon chosen under the MFEV approach.

We first examine the results when news shocks are identified as shocks that maximize the sum of FEVs of a particular variable under $0 \leq k \leq 40$. This forecast horizon is often adopted in the literature (see (Barsky and Sims, 2011) and (Kurmann and Otrok, 2013)). We then consider an alternative MFEV approach, under which we equalize the lower and the upper bound of the forecast horizon, i.e., $\underline{k} = \overline{k} = k$.

Figure 2.10 reports the IRFs of all the variables to the two news shocks under $0 \leq k \leq 40$. Interestingly, the two news shocks now incur significantly different IRFs for all variables under this alternative forecast horizon. Specifically, instead of following a slow diffusion process, TFP jumps up immediately in response to TFP news shocks and reaches its peak at a horizon of thirteen quarters after the initial impact. By contrast, the initial response of TFP to the news shock to PC is still negative and becomes positive only after around ten quarters. Another noticeable difference is the IRFs of macro variables to these two news shocks: the initial responses of hours worked and output to TFP news shocks are negative, whereas the impact responses of all macro variables to the identified news shock to PC are still positive. Furthermore, the long-run impact of TFP news shocks on all variables, except hours worked, is around half of their counterparts for news shocks to PC. These sharp differences suggest that the news shocks to TFP or PC identified under the forecast horizon $0 \leq k \leq 40$ are more likely to contain temporary disturbances than those under our baseline specification.

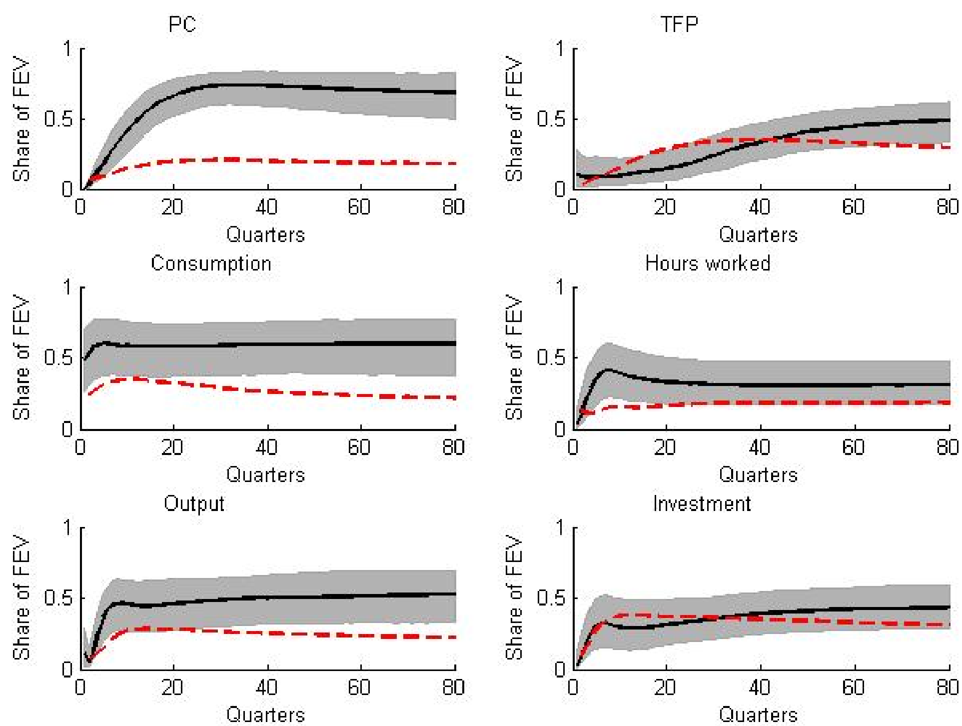
Turning to the FEVs of various variables to the two news shocks, we see that, throughout the forecast horizons, news shocks to TFP account for much less of the fluctuations of PC than news

Figure 2.10: Impulse Responses to News Shocks to PC and TFP Identified with the Range of Forecast Horizons $\bar{k} = 40$



Notes: IRFs to the news shock to PC (solid black line) and the TFP news shock (dashed red line) in the six-variable system with the range of forecast horizons $0 \leq k \leq 40$. The shaded gray area represents the 16-percent and 84-percent quantiles of the empirical distribution of the IRFs in the identification of the news shock to PC. The distribution is the bootstrapped impulse responses obtained through the residual-based resampling with 1,000 replications.

Figure 2.11: Share of FEV Decomposition Attributable to News Shocks to PC and TFP Identified with the Range of Forecast Horizons $k \in [0, 40]$



Notes: Forecast error variances (FEVs) to the news shock to PC (solid black line) and the TFP news shock (dashed red line) in the six-variable system with the range of forecast horizons $0 \leq k \leq 40$. The shaded gray area represents the 16-percent and 84-percent quantiles of the empirical distribution of the FEVs in the identification of the news shock to PC. The distribution is the bootstrapped FEVs obtained through the residual-based resampling with 1,000 replications.

shocks to PC (Figure 2.11). Also, the FEV of consumption, output, and in particular, hours worked explained by news shocks to TFP is much lower than the news shocks to PC. The only exception is TFP, which fluctuations in the short and medium runs are more accounted for by TFP news shocks than news shocks to PC.[49]

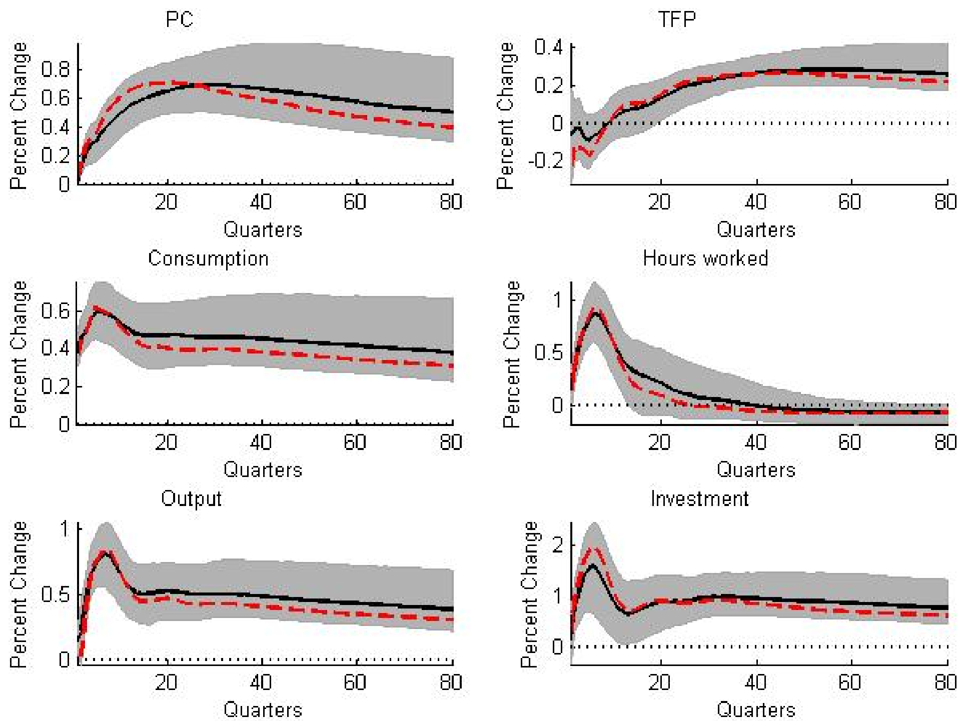
We generalize the above results by varying the upper bound of the forecast horizon, while maintaining the zero lower bound. The left two columns of Table 2.5 summarize the correlation of the two identified news shocks under different upper bounds of the forecast horizon. It is interesting to see that the correlation increases with the upper bound $\bar{k}$, which is consistent with the view of the slow diffusion of IST innovations. This suggests that our identified news shocks might capture shocks other than technological innovations—financial shocks, for example—if the upper bound of the forecast horizon under the MFEV approach is too small.

Which of our two identified news shocks is more sensitive to the choice of the upper bound of the forecast horizon? Figure 2.12 compares the IRFs to the news shock to PC under $\bar{k} = 40$ and 120. We see that the IRFs for each variable are fairly close. If any difference exists, the identified news shock under $\bar{k} = 120$ is quantitatively more important for all variables in the long run. The correlation coefficient of the identified news shocks to PC under these two scenarios is 0.9479. By contrast, the correlation coefficient of the news shock to TFP is sensitive to the choice of the upper bound: the correlation coefficient for TFP news shocks identified under $\bar{k} = 40$ and 120 is only 0.6597. This is intuitive since, over a short horizon, various shocks other than technological changes may underlie the identified news shock to TFP.

As proposed by Francis et al. (2012), another approach to identify news shocks that capture the long-run fluctuations in PC and TFP is to maximize the FEVs of TFP and PC at a finite, but long,

[49]Specifically, news shocks to TFP explain about 25 percent of TFP fluctuations 16 quarters ahead and about 40 percent of TFP fluctuations ten years ahead, a result reminiscent of the findings of Barsky and Sims (2011).

Figure 2.12: Impulse Responses to News Shocks to PC Identified with the Range of Forecast Horizons $k \in [0,40]$ and $k \in [0,120]$



Notes: IRFs to the news shock to PC in the case of $0 \leq k \leq 120$ (solid black line) and in the case of $0 \leq k \leq 40$ (dashed red line) under the six-variable system. The shaded gray area represents the 16-percent and 84-percent quantiles of the empirical distribution of the impulse response functions in the identification of the news shock to PC over the range of forecast horizons $0 \leq k \leq 120$. The distribution is the bootstrapped impulse responses obtained through the residual-based resampling with 1,000 replications.

Table 2.5: The Correlation of the News Shocks to TFP and PC Identified Under Alternative Forecast Horizons

$k \in [\underline{k}, \bar{k}]$	Corr. Coef.	$\underline{k} = \bar{k} = k$	Correlation Coefficient
$[0,40]$	0.4537	$k = 40$	0.9639
$[0,60]$	0.6079	$k = 60$	0.9916
$[0,80]$	0.8474	$k = 80$	0.9916
$[0,120]$	0.9773	$k = 120$	0.9956

Note: The correlation coefficients are obtained from extracting the news shocks to TFP and PC in the six-variable system with the range of forecast horizons as $\underline{k} \leq k \leq \bar{k}$.

forecast horizon. The results under this approach are reported in the right two columns of Table 2.5. Interestingly, under this alternative approach, the correlation coefficient of the two identified news shocks is robust to the choice of forecast horizon.[50] For example, at $\underline{k} = \overline{k} = 40$, the correlation coefficient of the two identified news shocks is 0.9639. Moreover, Figure 2.13 shows that the impulse responses of all macro variables to the two news shocks are very similar to their counterparts in the baseline specification. The potential reason behind this robustness of results, in contrast to the case with $0 \leq k \leq 40$, is that, by increasing the lower bound of the forecast horizon, those short-run disturbances to TFP are more likely to be insulated from the identified TFP news shocks. This allows TFP news shocks to capture more precisely shocks that drive the long-run movement of TFP.[51] Again, the high correlation of the two empirically identified news shocks under this alternative approach supports IST news shocks as a main source of anticipated TFP fluctuations.

To summarize, our findings about the quasi-identity of news shocks to PC and TFP are robust to alternative forecast horizons chosen under the MFEV approach, as long as both shocks are identified to capture the long-run variations of the corresponding variables. Moreover, under the zero lower bound of the range of forecast horizons, the correlation of the two news shocks increase monotonically with the upper bound of the forecast horizon under MFEV. All these findings support that IST news shocks as the common long-run shocks to TFP and PC are one main driver of anticipated TFP fluctuations.

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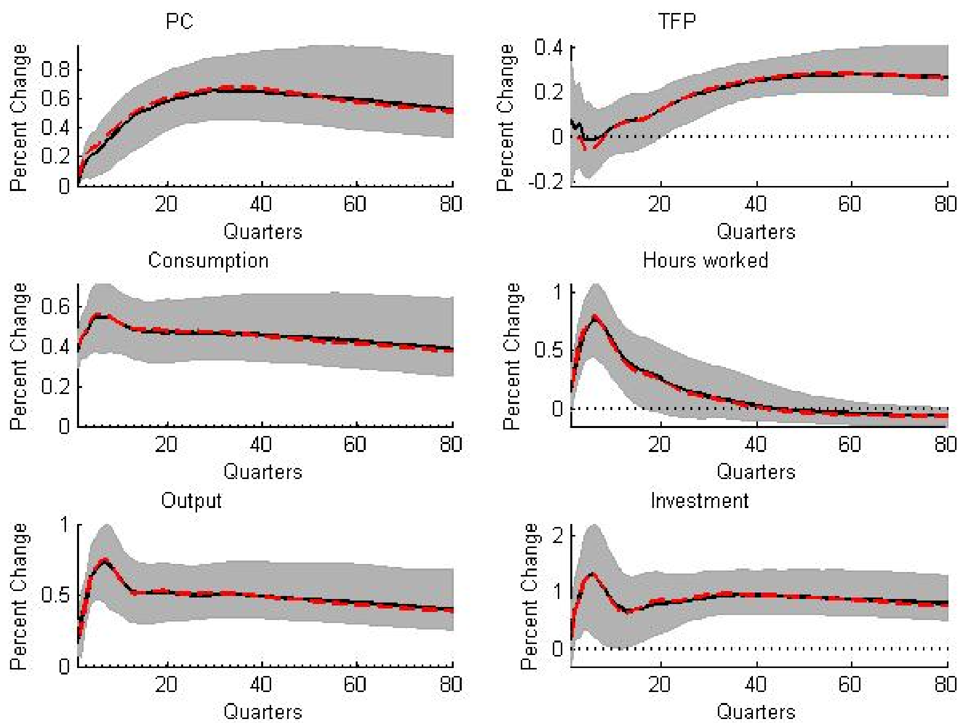
[50]We also compute the value of β according to equation (2.22) using the FEVs of TFP and PC attributable to news shocks to PC 120 quarters ahead. The value of β is around 0.93-0.95. This implies the robustness of the magnitude of the spillover effect to alternative MFEV specification.

[51]In addition, when $\underline{k} = 40$, the correlation coefficient is very robust to the choice of upper bound and remains above 0.95. For example, at $\overline{k} = 120$, the correlation coefficient is 0.9887.

Figure 2.13: Impulse Responses to the News Shocks to PC and TFP Identified with the Range of Forecast Horizons $\underline{k} = \overline{k} = 40$



Notes: IRFs to the news shock to PC (solid black line) and the TFP news shock (dashed red line) in the six-variable system with the range of forecast horizons $\underline{k} = \overline{k} = 40$. The shaded gray area represents the 16-percent and 84-percent quantiles of the empirical distribution of the IRFs in the identification of the news shock to PC. The distribution is the bootstrapped impulse responses obtained through the residual-based resampling with 1,000 replications.

Conclusion

This paper explores the quantitative importance of news about investment-specific technological changes in anticipated future TFP fluctuations. To this end, we identify two news shocks with the maximum forecast error variance approach: news shocks to TFP and news shocks to the inverse of the relative price of investment. We then map the identified news shocks into the primitive shocks in a model of IST spillover. A novel feature of the model is that innovations to the IST diffusion process influence the expected future TFP of not only the capital-producing sector, but also the consumption sector via spillover. Accordingly, the correlation of the two identified news shocks can be fruitful in distinguishing the quantitative importance of IST innovations in anticipated future TFP fluctuations.

Our main empirical finding using post-war U.S. data is that these two news shocks are almost perfectly collinear if both are identified to capture the long-run movement of the corresponding variables. The observed dynamics of TFP in response to a news shock to the inverse of the relative price of investment closely resembles its counterpart of a TFP news shock. Moreover, both shocks can explain a significant, and surprisingly similar, fraction of the fluctuations in other important macro variables over business cycles. Our findings suggest that embodied technological changes, which are general purpose, are important drivers of anticipated TFP fluctuations and U.S. business cycles.

Our findings highlight the potential fruitfulness of exploring why technological breakthroughs often originate in the capital-producing sector. Moreover, from both theoretical and empirical perspectives, more work is called for to uncover the channels through which IST innovations diffuse and enhance the productive efficiency of the rest of the economy and to quantify the importance of such channels for U.S. business cycles and asset pricing. Uncovering such a channel might also shed light on why outputs across different U.S. industries co-move together, a key feature of U.S. business cycles.

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Appendix 2.A: A Generalized Two-sector Model

Consider a decentralized two-sector economy in which one sector produces consumption goods and the other produces investment goods. Both sectors are comprised of monopolistically competitive firms. Firms in each sector rent capital and labor from competitive factor markets. For generality, assume that labor is not mobile across sectors, so that firms in each sector face a sector-specific wage rate, W_t^i, $i \in \{C, I\}$.[52] The production technology for each sector is Cobb-Douglas with sector-specific capital elasticity α_i.

The firm in each sector solves a cost minimization problem, given the physical output Y_t^i.

$$\min_{L_t^i, K_t^i} W_t^i L_t^i + R_t K_t^i$$

subject to

$$TFP_t^i \left(K_t^i\right)^{\alpha_i} \left(L_t^i\right)^{1-\alpha_i} \geq Y_t^i,$$

where TFP_t^i denotes technology specific to sector i. In this economy, an investment-specific technology (IST) shock Φ_t is isomorphic to a production technology for efficiency investment units with total factor productivity defined as $TFP_t^I \equiv TFP_t^C \Phi$.[53] The first-order conditions implies

$$\frac{K_t^i}{L_t^i} = \frac{\alpha_i}{1-\alpha_i} \frac{W_t^i}{R_t}. \tag{A.1}$$

[52]Similarly, we can assume that firms in each sector face a sector-specific rental rate of capital. This would not change our results.

[53]Guerrieri, Henderson, and Kim (2010) obtain the necessary condition for the equivalence between IST shocks and sectoral multifactor productivity shocks in an environment with machinery and nonmachinery output as intermediate input. The necessary condition is partial specialization in the assembly under which the assembly of consumption (and structure investment) use only non-machinery output; and the assembly of equipment is Cobb-Douglas in both outputs. Our model setup, as well as GHK, can be viewed as the limiting case of partial specialization, in which (equipment) investment assembly uses only machinery output.

Denote the marginal cost for goods in sector i as λ_t^i. The first-order conditions give

$$\lambda_t^i = \frac{1}{TFP_t^i}\left(\frac{W_t^i}{1-\alpha_i}\right)^{1-\alpha_i}\left(\frac{R_t}{\alpha_i}\right)^{\alpha_i},$$
$$= \frac{1}{TFP_t^i}\frac{W_t^i}{1-\alpha_i}\left(\frac{K_t^i}{L_t^i}\right)^{-\alpha_i}, \tag{A.2}$$

where the second equality comes from equation $(A.1)$.

Profit maximization by differentiated good producers gives

$$P_t^i = \mu_t^i \lambda_t^i \text{ for } i \in \{C, I\}, \tag{A.3}$$

where μ_t^i denotes the markup over unit production costs.

Combining equations $(A.2)$ and $(A.3)$, we obtain

$$\frac{P_t^C}{P_t^I} = \frac{\mu_t^C}{\mu_t^I}\frac{1-\alpha_I}{1-\alpha_C}\frac{W_t^C}{W_t^I}\left(\frac{K_t^C}{L_t^C}\right)^{-\alpha_C}\left(\frac{K_t^I}{L_t^I}\right)^{\alpha_I}\Phi_t. \tag{A.4}$$

Denote the wedge between the inverse of the relative price of investment and IST as

$$\omega_t + \varpi_t \equiv \log\frac{\mu_t^C}{\mu_t^I}\frac{1-\alpha_I}{1-\alpha_C}\frac{W_t^C}{W_t^I}\left(\frac{K_t^C}{L_t^C}\right)^{-\alpha_C}\left(\frac{K_t^I}{L_t^I}\right)^{\alpha_I}.$$

This gives equation (2.5).

Appendix 2.B: Decomposition of Aggregate TFP

From the production side of the national account identity, aggregate output is a Divisia index of sector-level output. Accordingly, the growth rate of aggregate output is a weighted average of the growth rate of each component of aggregate expenditure.

$$\frac{\Delta Y}{Y} = \left(1 - w^I\right)\frac{\Delta C}{C} + w^I \frac{\Delta I}{I}, \tag{A.5}$$

where $w^I = P^I I / \left(P^Y Y\right)$ is the share of investment goods in the aggregate value added at period t; $P^I I$ is the nominal expenditure on investment; and $P^C C$ is the nominal expenditure on consumption. $P^Y Y = P^C C + P^I I$ is total nominal output.

Define aggregate TFP as $TFP_t \equiv Y_t / \left(K_t^{\alpha} L_t^{1-\alpha}\right)$. Moreover, the production technology for each sector is given as

$$C_t = TFP_t^C \left(K_t^C\right)^{\alpha} \left(L_t^C\right)^{1-\alpha}, I_t = TFP_t^I \left(K_t^I\right)^{\alpha} \left(L_t^I\right)^{1-\alpha}.$$

Accordingly, the percentage change of real aggregate output, consumption, and investment can be decomposed as

$$\frac{\Delta Y}{Y} = \frac{\Delta TFP}{TFP} + \alpha\frac{\Delta K}{K} + (1-\alpha)\frac{\Delta L}{L}, \tag{A.6}$$
$$\frac{\Delta C}{C} = \frac{\Delta TFP^C}{TFP^C} + \alpha\frac{\Delta K^C}{K^C} + (1-\alpha)\frac{\Delta L^C}{L^C}, \tag{A.7}$$
$$\frac{\Delta I}{I} = \frac{\Delta TFP^I}{TFP^I} + \alpha\frac{\Delta K^I}{K^I} + (1-\alpha)\frac{\Delta L^I}{L^I}, \tag{A.8}$$

where $\frac{\Delta X}{X}$ denotes the percentage change of a variable X. Substituting equations $(A.6)$, $(A.7)$, and

$(A.8)$ into $(A.5)$ and then reordering, we have

$$\begin{aligned}\frac{\Delta TFP}{TFP} &= \left(1-w^I\right)\frac{\Delta TFP^C}{TFP^C} + w^I\frac{\Delta TFP^I}{TFP^I} \\ &\quad + \alpha\left[\left(1-w^I\right)\frac{\Delta K^C}{K^C} + w^I\frac{\Delta K^I}{K^I} - \frac{\Delta K}{K}\right] \\ &\quad + (1-\alpha)\left[\left(1-w^I\right)\frac{\Delta L^C}{L^C} + w^I\frac{\Delta L^I}{L^I} - \frac{\Delta L}{L}\right].\end{aligned} \tag{A.9}$$

Also, since $K_t = K_t^C + K_t^I$, $L_t = L_t^C + L_t^I$, we have

$$\begin{aligned}\frac{\Delta K}{K} &= \frac{RK^C/\left(P^Y Y\right)}{RK/(P^Y Y)}\frac{\Delta K^C}{K^C} + \frac{RK^I/\left(P^Y Y\right)}{RK/(P^Y Y)}\frac{\Delta K^I}{K^I}, \\ &= \frac{RK^C/\left(P^Y Y\right)}{\alpha}\frac{\Delta K^C}{K^C} + \frac{RK^I/\left(P^Y Y\right)}{\alpha}\frac{\Delta K^I}{K^I}, \\ &= \frac{P^C C}{P^Y Y}\frac{\Delta K^C}{K^C} + \frac{P^I I}{P^Y Y}\frac{\Delta K^I}{K^I},\end{aligned} \tag{A.10}$$

where the second and third equalities come from the following first-order conditions:

$$\alpha = RK^C/\left(P^C C\right) = RK^I/\left(P^I I\right) = RK/\left(P^Y Y\right).$$

Similarly, we have

$$\frac{\Delta L}{L} = \frac{P^C C}{P^Y Y}\frac{\Delta L^C}{L^C} + \frac{P^I I}{P^Y Y}\frac{\Delta L^I}{L^I}. \tag{A.11}$$

Substituting equations $(A.10)$ and $(A.11)$ into $(A.9)$, we obtain

$$\frac{\Delta TFP}{TFP} = \left(1-w^I\right)\frac{\Delta TFP^C}{TFP^C} + w^I\frac{\Delta TFP^I}{TFP^I}.$$

Using the log-difference approximation, we have equation (2.6).

Appendix 2.C: Derivation of Theoretical FEV

We now derive equations (2.16) and (2.18) in Section 3. Since we are interested in the FEV of TFP in the long run, without loss of generality, we drop the temporary disturbance ν_t^I in the IST process. As we will later show, including ν_t^I will not change the expression of FEVs for both TFP and PC as the forecast horizon goes to infinity.

Equations (2.12) and (2.13) imply

$$\log TFP_t = \beta \sum_{j=0}^{\infty} d_j^I \eta_{1,t-j}^I + \sum_{j=0}^{\infty} d_j^N \eta_{1,t-j}^N + \sum_{j=0}^{\infty} (\rho^N)^j \eta_{2,t-j}^N.$$

Accordingly, the k-step ahead forecast of TFP is

$$\log TFP_{t+k|t} = \beta \sum_{j=k}^{\infty} d_j^I \eta_{1,t+k-j}^I + \sum_{j=k}^{\infty} d_j^N \eta_{1,t+k-j}^N + \sum_{j=k}^{\infty} (\rho^N)^j \eta_{2,t+k-j}^N.$$

And the k-step ahead forecast error of TFP is

$$\log TFP_{t+k} - \log TFP_{t+k|t} = \beta \sum_{j=0}^{k-1} d_j^I \eta_{1,t+k-j}^I + \sum_{j=0}^{k-1} d_j^N \eta_{1,t+k-j}^N + \sum_{j=0}^{k-1} (\rho^N)^j \eta_{2,t+k-j}^N.$$

Accordingly, the forecast error variance of TFP k-step ahead, denoted by $\Omega_{TFP}(k)$, is

$$\Omega_{TFP}(k) = \beta^2 \sigma_{\eta_1^I}^2 \sum_{j=0}^{k-1} (d_j^I)^2 + \sigma_{\eta_1^N}^2 \sum_{j=0}^{k-1} (d_j^N)^2 + \sigma_{\eta_2^N}^2 \sum_{j=0}^{k-1} (\rho^N)^{2j}. \tag{A.12}$$

Therefore, the share of the variance of the k-step ahead forecast error attributable to $\eta_{1,t}^I$, denoted as $\Omega_{TFP,\eta_1^I}(k)$, is

$$\Omega_{TFP,\eta_1^I}(k) = \frac{\beta^2 \sigma_{\eta_1^I}^2 \sum_{j=0}^{k-1} (d_j^I)^2}{\Omega_{TFP}(k)}. \tag{A.13}$$

Plugging equations (2.11) and (2.12) into $(A.13)$ and then reorganizing, we have

$$\Omega_{TFP,\eta_1^I}(k) = \frac{\beta^2 \sigma_{\eta_1^I}^2 \left[(k-1) - 2\delta_I \left(\frac{1-\delta_I^{k-1}}{1-\delta_I} \right) + \delta_I^2 \left(\frac{1-\delta_I^{2k-2}}{1-\delta_I^2} \right) \right]}{B}, \tag{A.14}$$

where

$$
\begin{aligned}
B &= \beta^2\sigma^2_{\eta_1^I}\left[(k-1)-2\delta_I\left(\frac{1-\delta_I^{k-1}}{1-\delta_I}\right)+\delta_I^2\left(\frac{1-\delta_I^{2k-2}}{1-\delta_I^2}\right)\right] \\
&\quad +\sigma^2_{\eta_1^N}\left[(k-1)-2\delta_N\left(\frac{1-\delta_N^{k-1}}{1-\delta_N}\right)+\delta_N^2\left(\frac{1-\delta_N^{2k-2}}{1-\delta_N^2}\right)\right] \\
&\quad +\sigma^2_{\eta_1^N}\frac{1-(\rho^N)^{2k}}{1-(\rho^N)^2}.
\end{aligned}
$$

Dividing both the numerator and the denominator of the right-side of equation (A.14) by its numerator yields

$$\Omega_{TFP,\eta_1^I}(k)=\frac{1}{D}, \tag{A.15}$$

where

$$
\begin{aligned}
D = 1 &+ \frac{\sigma^2_{\eta_1^N}}{\beta^2\sigma^2_{\eta_1^I}}\frac{k-1-2\delta_N\left(\frac{1-\delta_N^{k-1}}{1-\delta_N}\right)+\delta_N^2\left(\frac{1-\delta_N^{2k-2}}{1-\delta_N^2}\right)}{k-1-2\delta_I\left(\frac{1-\delta_I^{k-1}}{1-\delta_I}\right)+\delta_I^2\left(\frac{1-\delta_I^{2k-2}}{1-\delta_I^2}\right)} \\
&+ \frac{\sigma^2_{\eta_2^N}}{\beta^2\sigma^2_{\eta_1^I}}\frac{\frac{1-(\rho^N)^{2k}}{1-(\rho^N)^2}}{k-1-2\delta_I\left(\frac{1-\delta_I^{k-1}}{1-\delta_I}\right)+\delta_I^2\left(\frac{1-\delta_I^{2k-2}}{1-\delta_I^2}\right)}.
\end{aligned} \tag{A.16}
$$

With $k\to\infty$, the second argument on the right-side of equation $(A.16)$ converges to $\sigma^2_{\eta_1^N}/\left(\beta^2\sigma^2_{\eta_1^I}\right)$ and the third argument converges to zero. Hence, we have $D\to 1+\sigma^2_{\eta_1^N}/\left(\beta^2\sigma^2_{\eta_1^I}\right)$, which delivers equation (2.16).

For the inverse of the relative price of investment, we have

$$
\begin{aligned}
\log PC_t &= \sum_{j=0}^{\infty} d_j^I\eta^I_{1,t-j}+\omega_t+\varpi_t \\
&= \sum_{j=0}^{\infty} d_j^I\eta^I_{1,t-j}+\sum_{j=0}^{\infty}(\rho^\omega)^j\upsilon_{2,t-j}+\sum_{j=0}^{\infty}\upsilon_{1,t-j}.
\end{aligned}
$$

Following similar steps as outlined above, we can derive the share of the forecast error variance of PC k-step ahead attributable to $\eta^I_{1,t}$ as

$$\begin{aligned}\Omega_{PC,\eta_1^I}(k) &= \frac{\sigma^2_{\eta_1^I}\sum_{j=0}^{k-1}(d_j^I)^2}{\sigma^2_{\eta_1^I}\sum_{j=0}^{k-1}(d_j^I)^2+\sigma^2_{\upsilon_2}\sum_{j=0}^{k-1}(\rho^\omega)^{2j}+k\sigma^2_{\upsilon_1}},\\ &= \frac{1}{1+\frac{\sigma^2_{\upsilon_2}\left(\frac{1-(\rho^\omega)^{2k}}{1-(\rho^\omega)^2}\right)}{\sigma^2_{\eta_1^I}\left[k-1-2\delta_I\left(\frac{1-\delta_I^{k-1}}{1-\delta_I}\right)+\delta_I^2\left(\frac{1-\delta_I^{2k-2}}{1-\delta_I^2}\right)\right]}+\frac{k-1}{k-1-2\delta_I\left(\frac{1-\delta_I^{k-1}}{1-\delta_I}\right)+\delta_I^2\left(\frac{1-\delta_I^{2k-2}}{1-\delta_I^2}\right)}\frac{\sigma^2_{\upsilon_1}}{\sigma^2_{\eta_1^I}}}.\end{aligned}$$

As $k \to \infty$, it is easy to see that the second argument in the denominator converges to zero, while the third argument converges to $\sigma^2_{\upsilon_1}/\sigma^2_{\eta_1^I}$. Therefore, as $k \to \infty$,

$$\Omega_{PC,\eta_1^I}(k) = \frac{1}{1+\sigma^2_{\upsilon_1}/\sigma^2_{\eta_1^I}}. \tag{A.17}$$

Appendix 2.D: Spillover in Both Directions

We now explore the validity of our measure of the importance of IST news shocks for aggregate TFP fluctuations; that is, the correlation of the two empirically identified news shocks, when productivity spillover may originate from both sectors. To nest spillover in both directions, we adopt an alternative specification in which sector-specific TFP follows some exogenous process. For simplicity, we drop permanent and transitory shocks to the relative price of investment other than IST shocks. Also, we drop all the stationary components of sector-specific technology.[54] We show that in this framework, the sign of the correlation of the two empirically identified news shocks measures the direction of spillover.

Specifically, consider the following data-generating process for sector-specific TFPs

$$\begin{bmatrix} \log TFP_t^C \\ \log TFP_t^I \end{bmatrix} = B \begin{bmatrix} \varepsilon_t^C \\ \varepsilon_t^I \end{bmatrix}, \tag{A.21}$$

where

$$B = \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix} \tag{A.22}$$

is a matrix of structural parameters. ε_t^j, for sector $j \in \{C, I\}$, captures the stochastic disturbance to TFP of sector j and will be specified below. To interpret news shocks to the relative price of investment, we would like to define the relative TFP of the investment sector, $\log \Phi_t \equiv \log TFP_t^I - \log TFP_t^C$, and map it into the primitive shocks according to equations $(A.21)$ and $(A.22)$. Accordingly,

$$\log \Phi_t = \varepsilon_t^I (B_{22} - B_{12}) - \varepsilon_t^C (B_{11} - B_{21}). \tag{A.23}$$

[54] Our measure of the magnitude and the direction of spillover still applies when there exists a wedge, either permanent or stationary, between the relative price of investment and IST, or when there exists stationary components to sector-specific technology.

Note that Φ_t hinges on both ε_t^I and ε_t^C due to the potential spillover in either direction. If there exists investment-specific technology, by its definition $B_{22} = 1 + B_{12}$, where the direct impact of IST on TFP^I is normalized to 1. $B_{12} > 0$ captures the spillover effect of IST on consumption-sector TFP. By contrast, if there is no investment-specific technology, then $B_{22} = B_{12}$; implying that ε_t^I has symmetric effects on the TFP of both sectors. Similarly, if there exists consumption-specific technology, by definition we have $B_{11} = 1 + B_{21}$, with the spillover effect captured by $B_{21} > 0$.

Similar to our benchmark model, under the standard Divisia definition of aggregate output, aggregate TFP can be decomposed as

$$\begin{aligned}
\log TFP &= w^I \log TFP_t^I + \left(1 - w^I\right) \log TFP_t^C, \\
&= F^C \varepsilon_t^C + F^I \varepsilon_t^I,
\end{aligned}$$

where $F^C \equiv w^I B_{21} + \left(1 - w^I\right) B_{11}$ and $F^I \equiv w^I B_{22} + \left(1 - w^I\right) B_{12}$. Note that, the larger is the spillover from IST to the consumption-sector TFP (B_{12}), the larger is F^I. Similarly, the larger is the spillover from the consumption-specific technology to investment-sector TFP (B_{21}), the larger is F^C.

Now, we assume that the stochastic disturbance to each sector's TFP contains a diffusion process:

$$\begin{aligned}
\varepsilon_t^I &= \sum_{i=0}^{\infty} d_i^I \eta_{1,t-i}^I, \\
\varepsilon_t^C &= \sum_{i=0}^{\infty} d_i^N \eta_{1,t-i}^N, \\
d_i^J &= 1 - (\delta_J)^i, 0 \leq \delta_J < 1,\ J = I \text{ or } N.
\end{aligned}$$

Again, $\eta_1^I \overset{i.i.d.}{\sim} N\left(0, \sigma_{\eta_1^I}^2\right)$ and $\eta_1^N \overset{i.i.d.}{\sim} N\left(0, \sigma_{\eta_1^N}^2\right)$. Both shocks are orthogonal to each other.

We now analytically derive the correlation of the two identified news shocks and establish the link between such a correlation and the relative importance of IST news shocks in anticipated future TFP fluctuations. According to our model, the shock maximizing the FEV of PC at $\underline{k} = \overline{k} \to \infty$

(with zero impact effect), which is our identified news shock to PC, simply maps into a linear combination of the two permanent technical shocks:

$$\tilde{\varepsilon}_t^{PC} = (B_{22} - B_{12})\,\eta_{1t}^{I} - (B_{11} - B_{21})\,\eta_{1t}^{N}.$$

Note that if there exists a consumption-specific technical shock (i.e., $B_{11} = 1 + B_{21}$), its impact on PC would be negative, because an improvement in consumption-specific technology tends to reduce the relative price of consumption to investment. Similarly, by maximizing the FEV of TFP at $k \to \infty$, the identified news shock is:

$$\tilde{\varepsilon}_t^{TFP} = F^I \eta_{1t}^{I} + F^C \eta_{1t}^{N}.$$

The correlation coefficient between the two identified news shocks can, therefore, be expressed as follows:

$$\begin{aligned}
\rho\left(\tilde{\varepsilon}_t^{PC}, \tilde{\varepsilon}_t^{TFP}\right) &= \frac{\sigma^2_{\eta_1^I}(B_{22}-B_{12})F^I - \sigma^2_{\eta_1^N}(B_{11}-B_{21})F^C}{\sqrt{\sigma^2_{\eta_1^N}(B_{11}-B_{21})^2 + \sigma^2_{\eta_1^I}(B_{22}-B_{12})^2}\sqrt{\sigma^2_{\eta_1^N}(F^C)^2 + \sigma^2_{\eta_1^I}(F^I)^2}}, \\
&= \frac{1}{\sqrt{1 + \frac{\sigma^2_{\eta_1^N}}{\sigma^2_{\eta_1^I}}\frac{(B_{11}-B_{21})^2}{(B_{22}-B_{12})^2}}\sqrt{1 + \frac{\sigma^2_{\eta_1^N}}{\sigma^2_{\eta_1^I}}\left(\frac{F^C}{F^I}\right)^2}} \\
&\quad - \frac{1}{\sqrt{1 + \frac{\sigma^2_{\eta_1^I}}{\sigma^2_{\eta_1^N}}\frac{(B_{22}-B_{12})^2}{(B_{11}-B_{21})^2}}\sqrt{1 + \frac{\sigma^2_{\eta_1^I}}{\sigma^2_{\eta_1^N}}\left(\frac{F^I}{F^C}\right)^2}}.
\end{aligned} \tag{A.24}$$

To understand equation $(A.24)$, consider two special cases. First, assume that there is only investment-specific technology. In this case, $B_{11} = B_{21} = F^C$. Accordingly, the correlation of the two news shocks becomes

$$\rho\left(\tilde{\varepsilon}_t^{PC}, \tilde{\varepsilon}_t^{TFP}\right) = \frac{1}{\sqrt{1 + \frac{\sigma^2_{\eta_1^N}}{\sigma^2_{\eta_1^I}}\left(\frac{B_{11}}{F^I}\right)^2}},$$

which is equivalent to equation (2.21), with $\beta \equiv F^I/B_{11}$ (and $\sigma^2_{\upsilon_1} = 0$ by assumption). Once again, the effect of IST news shock on aggregate TFP can be measured by the magnitude of $\beta^2\sigma^2_{\eta_1^I}$ relative to $\sigma^2_{\eta_1^N}$. Second, assume that there is only consumption-specific technology. In this case, $B_{22} = B_{12} = F^I$. Accordingly, the correlation of the two news shocks becomes

$$\rho\left(\tilde{\varepsilon}_t^{PC}, \tilde{\varepsilon}_t^{TFP}\right) = -\frac{1}{\sqrt{1 + \frac{\sigma^2_{\eta^I}}{\sigma^2_{\eta_1^N}}\left(\frac{B_{22}}{F^C}\right)^2}}.$$

Similarly, the effect of consumption-specific technology on aggregate TFP depends on the relative magnitude of $\sigma^2_{\eta^N}\left(F^C/B_{22}\right)^2$ relative to $\sigma^2_{\eta_1^I}$.

More generally, when there exists spillover from both sectors, the correlation of the two empirically identified news shocks depends on the relative magnitude of the spillover from each sector-specific technology. If the spillover from IST news shocks dominates the spillover from consumption-specific technology, that is, $\sigma^2_{\eta_1^I}\left(F^I\right)^2$ is large relative to $\sigma^2_{\eta_1^N}\left(F^C\right)^2$, then the magnitude of the first argument on the right-side of $(A.24)$ tends to dominate that of the second argument (in absolute value). Accordingly, the correlation is positive. On the other hand, if the spillover from consumption-specific technology dominates, the correlation becomes negative. Therefore, the sign of the correlation coefficient between the two empirically identified news shocks reveals whether IST news shocks or shocks to consumption-specific technology dominate the underlying common driving force of TFP and PC.

Appendix 2.E: The Measure of IST Spillover Effects

Finally, we derive the measure of IST spillover effects. To this end, we first derive β in equation (2.22). As $k \to \infty$, we have

$$\sigma^2_{PC} = \sigma^2_{\eta^I_1} + \sigma^2_{\upsilon_1}, \tag{A.18}$$

where σ^2_{PC} denotes the variance of the news shock to PC. By combining equations $(A.17)$ and $(A.18)$, we can solve for $\sigma^2_{\eta^I_1}$ as

$$\sigma^2_{\eta^I_1} = \Omega_{PC,\eta^I_1}(k) \times \sigma^2_{PC}, \tag{A.19}$$

where both arguments on the right side of equation $(A.19)$ can be computed from the data. Equation $(A.19)$ is intuitive: the contribution of the IST news shock to the variance of the news shock to PC equals the share of the forecast error variance of PC attributable by the news shock to PC times the variance of PC. Similarly, for aggregate TFP, we see that as $k \to \infty$,

$$\sigma^2_{TFP} = \sigma^2_{\eta^N_1} + \beta^2 \sigma^2_{\eta^I_1},$$

where σ^2_{TFP} denotes the variance of news shocks to TFP. With equation (2.16), it is easy to show that as $k \to \infty$,

$$\beta^2 \sigma^2_{\eta^I_1} = \Omega_{TFP,\eta^I_1}(k) \times \sigma^2_{TFP}. \tag{A.20}$$

Combining equation $(A.19)$ and $(A.20)$, we have

$$\beta = \sqrt{\frac{\Omega_{TFP,\eta^I_1}(k) \times \sigma^2_{TFP}}{\Omega_{PC,\eta^I_1}(k) \times \sigma^2_{PC}}}.$$

Then $\alpha = \beta - w^I$, where w^I can be computed from the U.S. data.

CHAPTER 3

EXPLAINING U.S. BUSINESS CYCLES: TFP NEWS SHOCK OR IST NEWS SHOCK

Abstract

In this paper, I attempt to gauge the importance of news shocks in U.S. business cycles. In particular, I am interested in determining whether mood swings, captured by an optimism shock, are associated with anticipated permanent changes in technology and whether they are a source of macroeconomic fluctuations as suggested by Beaudry, Nam and Wang (2011). I begin by using a combination of sign and zero restrictions to identify innovations in optimism and anticipated innovations in investment and then I explore the extent to which such innovations play a role in business cycles. The results indicate that, on the one hand, anticipated innovations in investment are important sources of fluctuations as they generate comovement in output, consumption, investment, and hours worked. On the other hand, innovations in optimism induce a negative response in investment and hours worked. In addition, the innovations in investment account for over 40 percent of the forecast errors of the relative price of investment, hours, output, investment, and consumption over a horizon of three to five years while the innovations in optimism play only a minor role. To ascertain the source of each innovation, I examine the link between the two shocks and major changes in total factor productivity and relative price of investment goods. Specifically, using the maximum forecast error variance approach, I isolate sequentially a TFP news shock and an IST news shock. I

find that there is a close link between the IST news shock and the anticipated innovations in investment. However, the equivalence between the optimism shock and the TFP news shock documented by Beaudry, Nam and Wang (2011) vanishes. What emerges is a similarity between the IST news shock and the TFP news shock, suggesting that there might exist a spillover effect arising from slowly diffusing innovations in investment-specific technology to TFP.

Introduction

The recent financial crisis of 2008 has brought to the forefront of economic research the elusive question of the major sources of fluctuations. The economic environment prior to the crisis was characterized by a burgeoning housing market, fueled by over-optimistic and unrealistic beliefs about future housing capital gains via the continuous appreciation of house prices. The experience is quite reminiscent of the 1990s, where the anticipation of profitability of future technologies in information and communication contributed to a large growth in investment and economic activity. These observations led researchers to propose that changes in expectations not necessarily related to improvements in technology might play an important role in explaining fluctuations. This notion dates back to Pigou (2199) has recently been rejuvenated by Beaudry, and Portier (2006), who have provided empirical evidence in support of the relevance of expectations in short-run fluctuations. Under the assumption that permanent increases in total factor productivity (TFP) are reflections of technology advances, the authors identify "news shocks" to neutral technology or disembodied technology as innovations in stock prices that are orthogonal to current TFP and highly correlated with permanent changes in TFP. Their results suggest that market participants are adept at predicting future advances in technology. However, their results appear to be inconsistent with predictions of RBC models to TFP news shocks. In fact, in response to good news about productivity, consumers feel wealthier (wealth effect) and increase their consumption and leisure. Labor supply falls and causes output to decrease. A reduction in output combined with an increase in consumption implies a decrease in investment. Therefore, good news about future productivity generates an economic bust. Consequently, Beaudry and Portier's findings have drawn large interest among macro-economists who have since then attempted to reconcile, both theoretically and empirically, the results with conventional views of business cycle theory. As such, many important questions remain unanswered. Are news shocks really capable of generating the comovement observed among macroeconomic variables? Furthermore, are the anticipated movements in TFP capturing technological innovations that are embodied or disembodied in new capital? In fact, advances in technology may not necessarily result in permanent increases in TFP, but rather through technological progress that is embodied in new capital. Hence, equating permanent changes in TFP to technological innovations raises issues of mismeasurement. Finally, what is the relative importance of news shocks to neutral technology and news shocks to investment-specific technology in regards to comovement and fluctuations?

In this paper, I attempt to provide answers to these questions through the lens of a vector autoregression (VAR) as it is common to do so in the news shock literature. The identification strategy builds upon the wealth of approaches that have been proposed to either establish or refute the importance of news shocks for macroeconomic fluctuations. Specifically, I proceed in two steps. In the first step, I identify an optimism shock and an anticipated investment shock. Similar to Beaudry, Nam and Wang (2011), I isolate the "optimism shock" as the shock that generates a positive instantaneous response in the stock price index and consumption but is not associated with any contemporaneous movements in measured TFP. This approach simply amounts to imposing a combination of sign and zero restrictions in an effort to capture optimistic mood swings that reflect agents' attitudes about potential forces that will positively affect future productivity. In addition to the optimism shock, I also identify an anticipated investment shock as the shock that is orthogonal to the optimism shock, induces a positive instantaneous response in investment, is not associated with any contemporaneous changes in the investment price index, and yet generates a negative subsequent response in the investment price index. This shock might reveal exogenous variations that stem either from technological factors specific to the production of investment goods or from disturbances to the process by which these investment goods are turned into productive capital, such as financial factors, as argued by Justiniano et al. (2010). At this point, aside from the assumption that such disturbances induce a zero on-impact response to the investment price index, I maintain an impartial view as to their ultimate source.

When I apply the identification approach to U.S. data over the period $1975-Q1$ to $2009-Q1$, I find that both shocks generate disparate results in terms of comovement. The optimism shock induces an immediate market boom that is accompanied by an increase in current consumption as assumed through positive sign restrictions. Investment and hours worked, however, decline on impact. Hence, the optimism shock appears to fail the s*ine qua non* requirement of any admissible source of a business cycle. Interestingly, the optimism shock generates slow and permanent changes in both the investment price index and TFP. For example, the response of the investment price index seems to be null on impact, then the index slowly declines and never reverts to its equilibrium level. The gradual and permanent reaction of TFP resembles a response to a news shock about future innovations in TFP; an argument that is proposed by Beaudry, Nam and Wang (2011, BNW hereafter) as an interpretation of the optimism shock. Contrary to the optimism shock, the anticipated investment shock successfully generates the comovement observed among macroeconomic variables: consumption, investment, and hours worked increase on impact. Similar to the optimism shock, the anticipated investment shock also induces a gradual and permanent response on the investment price index and TFP. The news shock story might therefore be another potential interpretation for the anticipated investment shock as well. In sum, as far as comovement is concerned, the anticipated investment shock appears to stand as the most plausible candidate as the source of business cycles.

The same message is conveyed by the forecast error variance (FEV) decomposition. While the optimism shock explains only a very negligible portion—less than 5 percent—of the FEV of consumption, investment, and hours worked at horizons beyond 10 quarters, the anticipated investment shock accounts for more than 50 percent of the FEV of the macro variables. Furthermore, the anticipated investment shock plays a significant role for the investment price index and TFP as it explains 40 percent and 25 percent of their FEV, respectively. Surprisingly, the optimism shock also accounts for 15 percent of the FEV in the investment price index, but plays only a minor role for TFP—less than 5 percent of the TFP's FEV is attributable to the optimism shock. Overall, the results of this first step paint a clear picture. The anticipated investment shock emerges as the most important source of business cycle fluctuations among the two identified shocks, as it induces co-movement among consumption, investment, and hours worked. In addition, the dynamics of the investment price index and TFP to both shocks suggest that the two shocks might be interpreted as news shocks about future innovations in TFP and/or the investment price index.

Consequently, in the second step, I formally explore the news shock interpretation for the optimism shock and the anticipated investment shock. BNW suggests that the optimism shock is a shock to future TFP growth and is identified via the version of the maximum forecast error variance approach introduced by Francis et al. (2012). I will refer to this approach as the FMJR approach. Specifically, the method aims to isolate a shock that maximizes the forecast error variance of TFP attributable to that shock at a long but finite forecast horizon such that the shock initially has no impact on TFP. I will apply the same approach to both TFP and the investment price index to identify a TFP news shock and IST news shock, respectively; however, I will first isolate *sequentially* the shock that maximizes its contribution to the forecast error variance of TFP and the investment price index not only at a given horizon, but also at all horizons up to that given truncation point.[1] This approach has been proposed by Barsky and Sims (2011) and has been recently used by Kurmann and Otrok (2013)—I will refer to it as the BAS approach. The two approaches differ in terms of their treatments of the choice of the forecast horizon.

When I apply the BAS approach to identify the TFP news shock and the IST news shock,

[1] I will also impose the additional restriction that the IST news shock has no effect on TFP on impact.

the results depict a dichotomous picture. In the case of the IST news shock, the stock price index, consumption, investment, and hours respond positively on impact to the IST news shock. The co-movement of the macro variables appears to be consistent with what is observed in the case of the anticipated investment shock. A look at the dynamics of the investment price index and TFP to the IST news shock illustrates responses that are very similar to those obtained from the anticipated investment shock. For instance, TFP does not respond initially to the IST news shock, but it gradually increases and settles at a higher and permanent level. The same dynamics are observed with the investment price index with a slow and permanent decline rather than an increase. Furthermore, the share of the FEV of TFP, consumption, investment, and hours worked that is attributable to the IST news shock is quite identical to their counterparts from the anticipated investment shock. In other words, the IST news shock accounts for 50 percent of the FEV of the macro variables and 25 percent of the FEV of TFP. Similar responses are obtained when I apply the FMJR approach. These findings seem to suggest that the identified investment shock is in fact news about investment-specific technology. In the case of the TFP news shock, the results depict a murkier picture. The stock price index, consumption, and investment increase on impact to the TFP news shock, while hours worked declines. The initial increase of investment to the TFP news shock, although insignificant, casts some doubt to the interpretation that the optimism shock is a TFP news shock. In fact, the news shock accounts for a sizable portion of the FEV of macro variables while the optimism shock does not. In addition, the correlation between the two shocks is quite small—about 0.34. When the FMJR approach is applied, the impact response of hours to the TFP news shock is reversed from negative to positive; however, this only adds complications to the difficult task of establishing the hypothesis that the optimism shock might be a TFP news shock.

So, what do we learn from these results? First of all, the notion that episodes of optimism and pessimism are associated with future improvements in technology and are a plausible source of business cycle fluctuations remains an open-ended question. The results from BNW provide new evidence that appears to clarify the source of the differences among empirical studies aimed at understanding the role of beliefs and news in business cycle fluctuations. In fact, in regards to the role of the TFP news shock in generating comovement among macro variables, Barsky and Sims (2011) arrive at substantially different conclusions from BNW. Specifically, applying the BAS approach, they find that output, hours, and investment decline on impact while consumption rises. Furthermore, after the initial impact, the dynamic path of the variables largely tracks, as opposed to anticipates, the estimated path of TFP as claimed by Beaudry, and Portier (2006) and BNW. However, the latter authors suggest that the supposed difference simply stems from the choice of the forecast horizon in the maximum forecast error variance identification approach. They argue that the BAS approach is "inadequate" in isolating the TFP news shock because it is prone to picking factors that have short-term temporary effects on TFP instead of shocks that induce a gradual and permanent reaction to TFP. Beaudry, and Portier (2006), as well as BNW state that when the FMJR approach is used, the identified TFP news shock resembles the optimism shock as they both generate similar dynamics in macro variables that are consistent with the comovement observed in the data. However, their results do not appear to be robust to the identification of an additional source of variation. Once the investment shock is isolated in addition to the optimism shock, the comovement between the macro variables quickly vanishes and the optimism shock stops accounting for the FEV of TFP. The anticipated investment shock, which is established to be an IST news shock, on the other hand, emerges as the potential source of business cycle fluctuations. Furthermore, the TFP news shock generates comovement among macro variables, explains a sizable portion of the FEV in macro variables, induces a slow and permanent response in both TFP and the investment price index, and plays a role in explaining fluctuations in the investment price index. This in turn raises some questions in regards to the nature and source of the TFP news shock. To investigate this, I explore the correlation between the IST news shock and the TFP news shock since they induce similar dynamics to the variables of the system. It turns out that both shocks are highly correlated—the correlation coefficient is 0.97. This seems to suggest that the two shocks might be driven by a common factor. This argument is emphasized in a concurrent paper by Chen and Wemy (2014), who argue that the close correlation between the TFP news shock and the IST news shock is a consequence of spillover effect arising from slowly diffusing innovations in investment-specific technology (IST) to TFP. This line of reasoning is consistent with the argument that embodied technological progress is a General Purpose Technology (GPT); that is, a new invention that leads to fundamental changes in the production process of industries using it.

The remainder of the paper is structured as follows. In Section II, I describe the identification approach used to identify the optimism shock and the anticipated investment shock. I also discuss the data, the restrictions used in the identification process, and the results associated with the identified shocks. In Section III, I describe the maximum forecast error variance identification approach applied to isolate the TFP news shock and the IST news shock and then present the results in terms of impulse responses and variance decomposition. Section IV contains robustness checks to gauge the sensitivity of the results to different specifications and alternative measurements of some of the variables of the system. Finally, summarizing comments are in Section V.

Optimism Shock and Anticipated Investment Shock

In this section, I briefly describe the empirical approach used to isolate the optimism shock and the anticipated shock using signs and zeros restrictions. Much of the discussion is drawn from Uhlig (2003) and Mountford and Uhlig (2009). I, then present the data and discuss the empirical results.

Identification Approach: sign and zero restrictions

Most macroeconomic time series data can be well-approximated by a VAR(p)of the form:

$$Y_t = B_1 Y_{t-1} + \ldots + B_p Y_{t-p} + U_t, \tag{3.1}$$

where Y_t is a $N \times 1$ vector of observables at date t = 1-p,...,T; $B_i, i = 1, \ldots, p$ are coefficient matrices of size $N \times N$; and U_t is a $N \times 1$ vector of one-step-ahead prediction errors with a variance-covariance matrix $E[U_t U_t'] = \Sigma$. Deterministic and exogenous terms are ignored to save on notation. The vector moving average representation of equation (3.1) is:

$$Y_t = C(L) U_t \tag{3.2}$$

where $C(L) = [B(L)]^{-1} \equiv [I - B_1 L - \ldots - B_p L^p]^{-1}$ and $C(L) \equiv I - C_1 L + C_2 L^2 + +C_2 L^2 + \ldots$ Equation (3.2) can be consistently estimated using ordinary least squares, which when conditional on Gaussian U_t and initial conditions, is equal to the maximum likelihood estimator (MLE). Identification of the structural shocks amounts to finding a mapping A_0 between the prediction errors U_t and a vector of mutually orthogonal shocks ε_t, such that $U_t = A_0 \varepsilon_t$, and the restriction $\Sigma = E[A_0 \varepsilon_t \varepsilon_t' A_0^{'}] = A_0 A_0^{'}$ is satisfied. This restriction is, however, not sufficient to identify A_0 because for any matrix A_0, there exists some alternative matrix $\tilde{A}$, such that $\tilde{A} Q = A_0$, where Q is an orthonormal matrix that also satisfies $\Sigma = \tilde{A}\tilde{A}'$. This alternative matrix maps U_t into another vector of mutually orthogonal shocks $\tilde{\varepsilon_t}$; that is, $U_t = \tilde{A}\tilde{\varepsilon}_t$. For some arbitrary matrix $\tilde{A}$ satisfying $\Sigma = \tilde{A}\tilde{A}'$,[2] identification is therefore reduced to choosing an orthonormal matrix Q.

In the VAR literature, identification usually proceeds by identifying all N fundamental shocks, thus characterizing the entire A_0 matrix. This requires imposing $N(N-1)/2$ restrictions on A_0. For the present analysis, however, I follow the method of Uhlig (2003) and identify at most

[2]Possible candidates for $\tilde{A}$ are the Choleski decomposition or the eigenvalue-eigenvector decomposition of Σ

two fundamental shocks, leading to the need to characterize only two columns of the A_0 matrix $[a^1, a^2]$.

The implied structural moving average representation can be written as:

$$Y_t = \sum_{h=0}^{\infty} R_h \tilde{\varepsilon_{t-h}}, \tag{3.3}$$

where $R_h = C_h \tilde{A} Q$.

Therefore, the impulse response vector to a structural shock that corresponds to the j^{th} element of $\tilde{\varepsilon}_t$ is the j^{th} column of R_h, denoted by:

$$r_j(h) = C_h \tilde{A} q_j, \tag{3.4}$$

where q_j is the j^{th} column of Q. Also, the impulse response of variable i to structural shock j at horizon h is the i^{th} element of $r_j(h)$ denoted by:

$$r_j^i(h) = C_h^i \tilde{A} q_j, \tag{3.5}$$

where C_h^i is the i^{th} row of C_h.

Define the function f on the real line such that $f(x) = 100x$, if $x \geq 0$ and $f(x) = x$, if $x \leq 0$. Let σ_i be the standard error of variable i. Let (J_+) be the index set of variables for which identification of a given shock restricts the impulse response to be positive,and let (J_-) be the index set of variables for which identification restricts the impulse response to be negative. Hence, to impose the sign restrictions, I will solve the following problem:

$$q^* = argmin \Psi(q) \quad s.t \quad q'q = 1, \tag{3.6}$$

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

$$\Psi(q) = \sum_{j \varepsilon J_+} \sum_{k=0}^{H} f\left(-\frac{r_j^i(h)}{\sigma_i}\right) + \sum_{j \varepsilon J_-} \sum_{k=0}^{H} f\left(\frac{r_j^i(h)}{\sigma_i}\right) \tag{3.7}$$

Zero impact restrictions, where the response of the investment price index to the anticipated investment shock and the response of TFP to the optimism shock can be easily incorporated by modifying the constraint such that:

$$Gq = 0, \tag{3.8}$$

where G is the (1×2) vector of the form

$$G = [r_1^1(0) \quad r_2^2(0)] \tag{3.9}$$

To identify the columns $[q^1, q^2]$ associated with the matrix $[a^1, a^2]$, I first identify the anticipated investment shock in the manner described above and then identify the second shock by replacing the minimization problem in equation (3.6). Thus,

$$q^2 = argmin\Psi(q) \quad s.t \quad q'q = 1, Gq = 0, q^1 q^2 = 0, \tag{3.10}$$

where the first constraint guarantees that q is a unit-length column vector that belongs to an orthonormal matrix, the second restriction imposes the zero on-impact response, and the third restriction ensures that the two shocks are orthogonal to each other.

In line with much of the literature, I use a Bayesian approach for estimation and inference with my prior and posterior belonging to the Normal-Wishart family. More specifically, I take a number of draws from the posterior distribution of the VAR coefficients and the variance-covariance matrix Σ. From each draw, the shocks are identified using the minimization problems (3.6) and (3.10). Given the sample of draws for the impulse responses and forecast errors variance decomposition, confidence bands can be plotted around the median responses and variance decompositions.

Data and Restrictions

The empirical exercise uses U.S. data over the period 1961:Q3 to 2008:Q4. The baseline specification consists of six variables. The two key series are the investment price index and a measure of total factor productivity. To measure the importance of the shocks to macro variables, I also include consumption, hours worked, and investment in the VAR system. Finally, I also include an index of the stock market value (SP) to capture market participants' beliefs about future economic development.

The investment price index corresponds to the ratio of the chain-weighted deflators for investment and consumption, which is taken from Justiniano, Primiceri and Tambalotti (2011). The numerator is the National Income and Product Accounts (NIPA) deflator for durable consumption and private investment. However, Gordon (2199) and Cummins and Violante (2002) argue that NIPA's quality adjustments may underestimate the rate of technological progress in areas such as equipment and software—an issue that can distort the measured contribution of IST changes to both growth and business cycles. Consequently, Gordon constructed the alternative price series for producer durable equipment, which was later updated by Cummins and Violante (GCV deflator hereafter). For the baseline model, I work with the NIPA deflators; however, I also check the robustness of the results using the GCV deflator.[3]

The series of aggregate TFP growth is taken from Fernald (2012) and is measured as the growth rate of business–sector TFP.[4] I would like the TFP series to proxy for technological changes. Therefore, the TFP series are corrected for capital utilization. The main findings below are robust to the choice of TFP series unadjusted for capital utilization.

The consumption measure C is the per capita value of the real personal consumption of non-

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[3] I thank Patrick Higgins from the Federal Bank of Atlanta for sharing the updated series of GCV deflators.

[4] The data is updated on John Fernald's webpage: http://www.frbsf.org/economic-research/economists/john-fernald/.

durable goods and services. Investment measure I is the per capita value of the sum of real personal consumption of durable goods and real fixed private domestic investment. Hours H is per capita hours worked in the nonfarm business sector.[5] Output Y is GDP per capita. I use the corresponding chain-weighted deflators to obtain the real series. All per capita series are obtained by dividing the corresponding aggregate variables by the civilian non-institutional population aged 16 and above which is obtained from the Bureau of Labor Statistics. Finally, the measure of the stock price index is the per capita real S&P 500 index. The S&P 500 composite index is taken from Robert Shiller's webpage. The price deflator is the price index for gross value added in the non-farm business sector, taken from the Bureau of Economic Analysis (Table 1.3.4). The stock index is converted to a quarterly frequency by taking the average of the monthly stock index over each quarter.

I estimate a vector auto-regression (VAR) in level of all variables in the baseline specification. I prefer the level specification because, while several of these series appear to be $I(1)$, estimating the system in levels will produce consistent estimates of impulse responses and is robust to the cointegration of unknown forms.[6] According to standard likelihood methods, four or five appears to be the optimal lag order when testing in an ascendant way for the optimal number of lags from two quarters up to three years. I therefore choose to work with four lags in our baseline model; however, all the results are robust to adopting a five-lag specification.

I isolate the optimism shock and the anticipated investment shock using the following sign and zero restrictions. Similar to Beaudry, Nam and Wang (2011), I impose the restriction that the "optimism shock" generates a positive instantaneous response in the stock price index and consumption, but is not associated with any contemporaneous movements in measured TFP. As pointed out by the authors, this identification is not very restrictive because a monetary policy shock can

[5]The data for hours is taken from Valerie Ramey's webpage: http://econweb.ucsd.edu/˜vramey/research.html#data.

[6]Moreover, according to Fisher (2010), invalid assumptions concerning common trends may produce misleading results.

induce the same response in the stock price index, consumption, and TFP. Since the results for this least restrictive case are identical to the most restrictive case when the real interest rate is not allowed to be non-negative on impact, I simply adopt the former. In addition, I impose the restriction that the "anticipated investment shock" is orthogonal to the optimism shock, induces a positive instantaneous response in investment, is not associated with any contemporaneous changes in the investment price index, and yet generates a negative subsequent response in the investment price index. This shock may reflect exogenous variations that stem either from technological factors specific to the production of investment goods or investment-specific technological change) or from disturbances to the process by which these investment goods are turned into productive capital, such as financial factors or changes to the marginal efficiency of investment. Greenwood, Hercowitz and Krusell (1997) and Fisher (2006) have argued for an important role of the former, which makes investment goods progressively cheaper, as a primary force behind business cycles. On the other hand, Justiniano, Primiceri and Tambalotti (2011) have recently found that the latter shock is the prime driver of investment and output. At this point, except for the assumption that such exogenous variations are anticipated by economic agents, I maintain an agnostic view on their ultimate source. The restrictions are summarized in Table(3.1).

Table 3.1: Sign and Zero Restrictions

	TFP	Inv. price Index	Stock price	Consumption	Investment
Optimism shock	0		$+$	$+$	
Anticipated investment shock		0 then $-$			$+$

Results: Dynamic Effects of the Optimism Shock and Anticipated Investment Shock

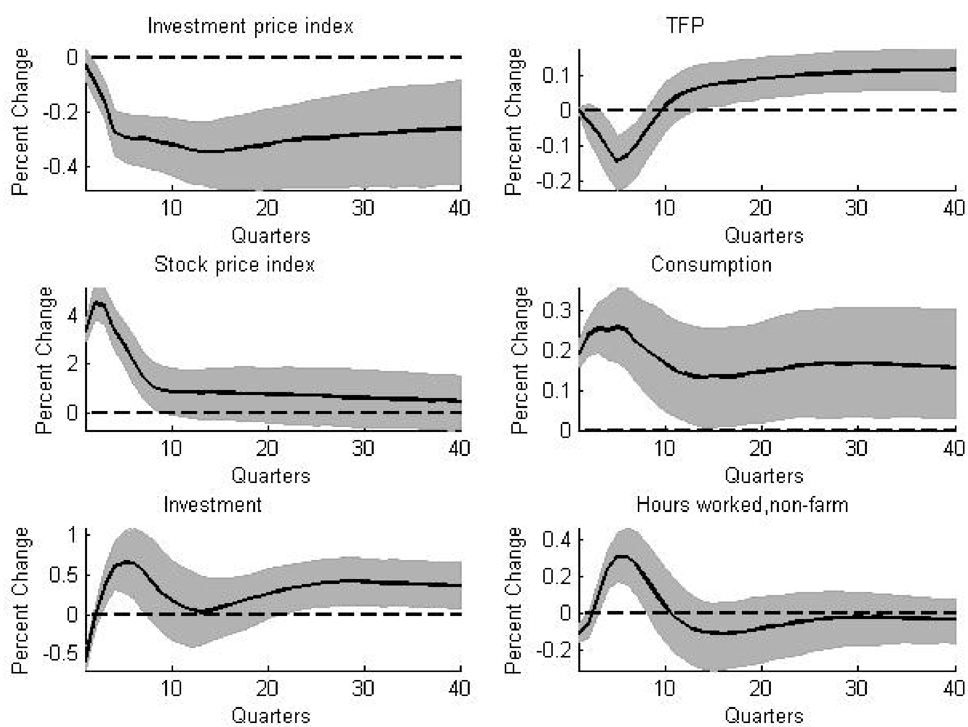
The estimated impulse responses to the optimism shock and the anticipated investment shock obtained under the sign and zero restrictions are presented in Figure (3.1) and Figure (3.2).

In each case, the figure shows the median (solid line) and the $16th$ and $84th$ percentiles (shaded gray region) of the point-wise posterior distribution of the impulse responses of the variables of the system.

In Figure (3.1), the optimism shock generates an immediate market boom that is accompanied by an increase in current consumption as assumed through the positive sign restrictions. Also, the impact response of TFP to the shock is null by assumption, then slowly rises to a higher permanent level. These dynamics are fairly similar to those reported in BNW. However, there are some differences between the two studies. Specifically, investment and hours worked decline on impact in the present study, whereas they increase in BNW. Such differences cast some doubt on their argument that the optimism shock is a TFP news shock because the gradual and permanent reaction of TFP resembles a response to a news shock about future innovations in TFP. Nonetheless, I will formally verify this interpretation in the next section. Hence, in terms of comovement, the optimism shock appears to fail the *sine qua non* requirement of any admissible source of business cycles. Contrary to the optimism shock, the anticipated investment shock successfully generates the comovement observed among macroeconomic variables. As illustrated in Figure (3.2), consumption, investment, and hours worked increase on impact. Similar to the optimism shock, the anticipated investment shock also induces a gradual and permanent response to the investment price index and TFP. The dynamics of the investment price index closely resembles that of a news shock about investment-specific technology, or IST news shock. Ben-Zeev and Khan (2013) argue that the IST news shock is an important source of business cycle fluctuations. As opposed to the optimism shock, the equivalence between the anticipated investment shock and the IST news shock is more plausible because of the comovement that the anticipated investment shock generates among macro variables.

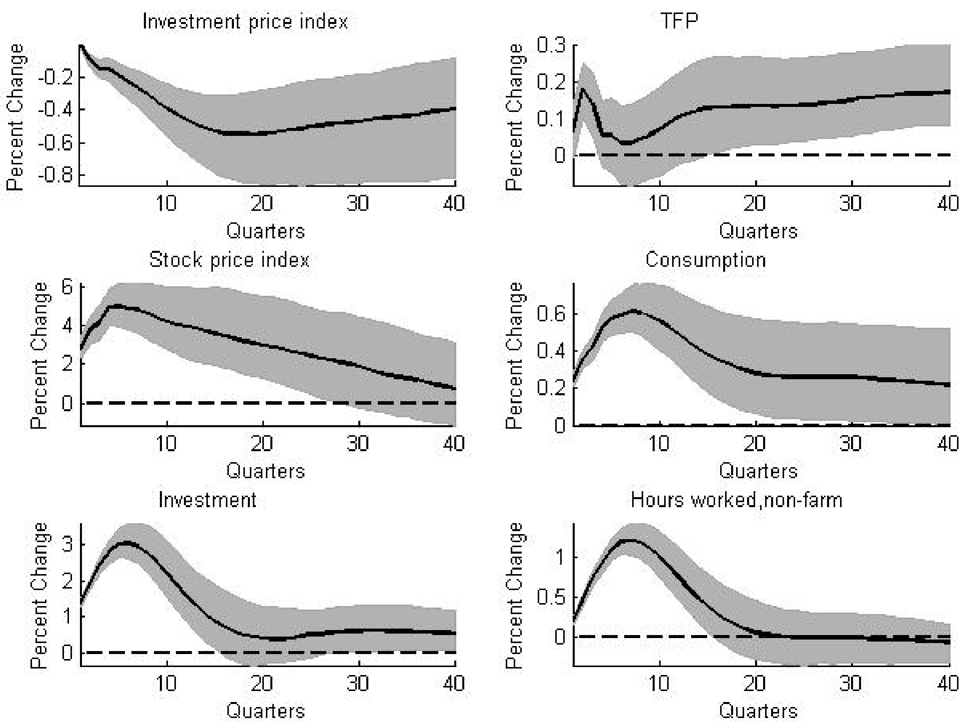
To confirm the results exhibited by the impulse responses, I present the forecast error vari-

Figure 3.1: Impulse responses to a 1 percent innovation in the optimism shock



Notes: The solid line represents the median response of the variables, while the shaded gray region represents the 16^{th} and 84^{th} percentile coverage from the empirical distribution of impulse responses.

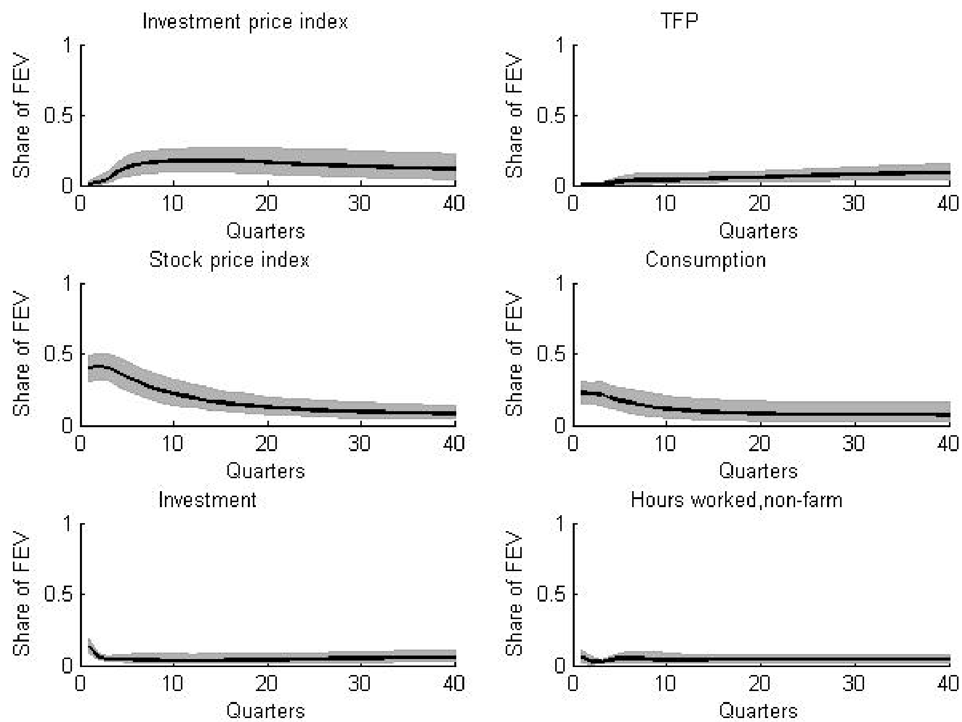
Figure 3.2: Impulse Responses to a 1 percent innovation in the anticipated investment shock



Notes: The solid line represents the median response of the variables, while the shaded gray region represents the 16^{th} and 84^{th} percentile coverage from the empirical distribution of impulse responses.

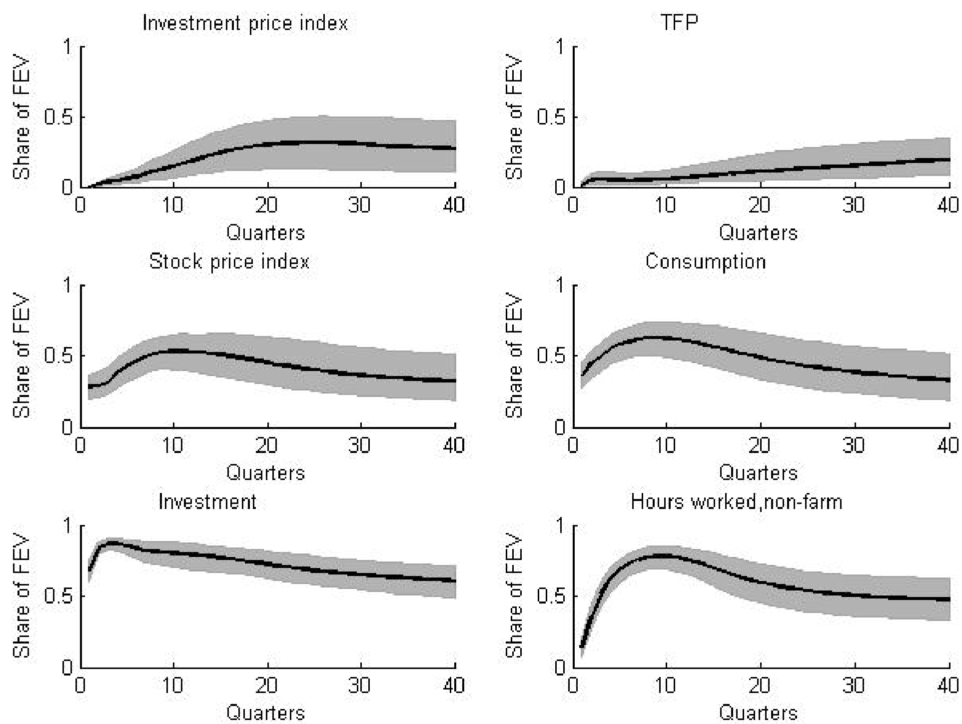
ance (FEV) of the variables of the system that is attributable to each shock. The share of the FEV accounted for by the optimism shock and the anticipated investment are displayed in Figure(3.3) and Figure(3.4) respectively. Similar to the impulse responses, the FEVs indicate that the anticipated investment shock plays the most significant role in aggregate fluctuations among the two shocks. For example, the optimism shock explains only a very negligible portion—less than 5 percent—of the FEV of consumption, investment, and hours worked at horizons beyond 10 quarters, while the anticipated investment shock accounts for more than 50 percent of the FEV of the macro variables. Furthermore, the anticipated investment shock plays a significant role for the investment price index and TFP as it explains 40 percent and 25 percent of their FEV, respectively. Surprisingly, the optimism shock also accounts for 15 percent of the FEV in the investment price index, but play only a minor role for TFP—less than 5 percent of TFP's FEV is attributable to the optimism shock. Overall, it appears that episodes of mood swings captured by the optimism shock do not pass the test for being potential sources of business cycle fluctuations.

Figure 3.3: Share of the Forecast Error Variance to a 1 percent innovation in the optimism shock



Notes: The solid line represents the median share of the FEV of the variables, while the shaded gray region represents the 16^{th} and 84^{th} percentile coverage from the empirical distribution of FEVs.

Figure 3.4: Share of the Forecast Error Variance to a 1 percent innovation in the anticipated investment shock



Notes: The solid line represents the median share of the FEV of the variables, while the shaded gray region represents the 16^{th} and 84^{th} percentile coverage from the empirical distribution of FEVs.

TFP News Shock and IST News Shock

In this section, I briefly introduce the identification approach used to isolate the TFP news shock and the IST news shock. The main goal is to explore: 1) The supposed interpretation that the optimism shock is a TFP news shock; and 2) The hypothesis that the anticipated investment shock might be capturing a gradual and permanent diffusion process about technological progress that is embodied in capital. The BAS approach has been used recently by Barsky and Sims (2011) and Ben-Zeev and Khan (2013) in the identification of a TFP news shock and an IST news shock, respectively. I will also highlight the difference between the BAS approach and the alternative, yet similar FMJR approach.

Identification Approach: VAR Basics

I will apply the approach sequentially to identify the IST news shock and the TFP news shock. The only difference is that the target variable will be the investment price index in the identification the of IST news shock while TFP will be the target variable for the TFP news shock. Consequently, without loss of generality, let the investment price index be the first element of Y_t and let q_1 denote the unit vector associated with the IST news shock. Assuming that there exists a shock (the IST news shock) that does not have an immediate impact on the investment price index, but becomes an important factor in the investment price index over the forecast horizon $\left[\underline{k}, \overline{k}\right]$, I can identify such a shock by finding a column q_1 of Q that explains the sum of the FEVs of the investment price index over the horizon $\left[\underline{k}, \overline{k}\right]$. Specifically, I solve the following maximizing problem, given the Cholesky decomposition of Σ, $\tilde{A}$:

$$q_1 = argmax \;\; q_1' S q_1 \equiv q_1' [\sum_{k=\underline{k}}^{\overline{k}} \sum_{l=0}^{k} \tilde{A}' C_l' (e_i e_i') C_l \tilde{A}] q_1, \tag{3.11}$$

subject to

$$q_1' q_1 = 1, \tag{3.12}$$

$$q_1^{(1)} = 0, \tag{3.13}$$

where S is the sum of the variances of the k-step ahead forecast error of the investment price index over the forecast horizon $k \in [\underline{k}, \overline{k}]$.[7] The first constraint guarantees that q_1 is a unit-length column vector that belongs to an orthonormal matrix, while the second constraint imposes the restriction that the shock has no contemporaneous effect on the level of the investment price index. This problem can be written as a quadratic form in which the non-zero portion of q_1 is the eigenvector associated with the largest eigenvalue of the $(m-1) \times (m-1)$ submatrix of S.

The FMJ approach also consists of solving the above problem, except that S now becomes:

$$S = \sum_{l=0}^{k} \tilde{A}' C_l' (e_i e_i') C_l \tilde{A}. \tag{3.14}$$

In other words, the FMJR approach maximizes the FEV of the investment price index at a long but finite forecast horizon k.

I estimate the VAR with the same six variables with four lags: the investment price index, a measure of total factor productivity, consumption, an index of the stock market value (SP), consumption, hours worked, and investment. To remain consistent with the BAS approach, I let the lower bound of the forecast horizon $\underline{k}$ in equation (3.11) be zero and I set the upper bound of the forecast horizon to $\overline{k} = 40$ quarters.

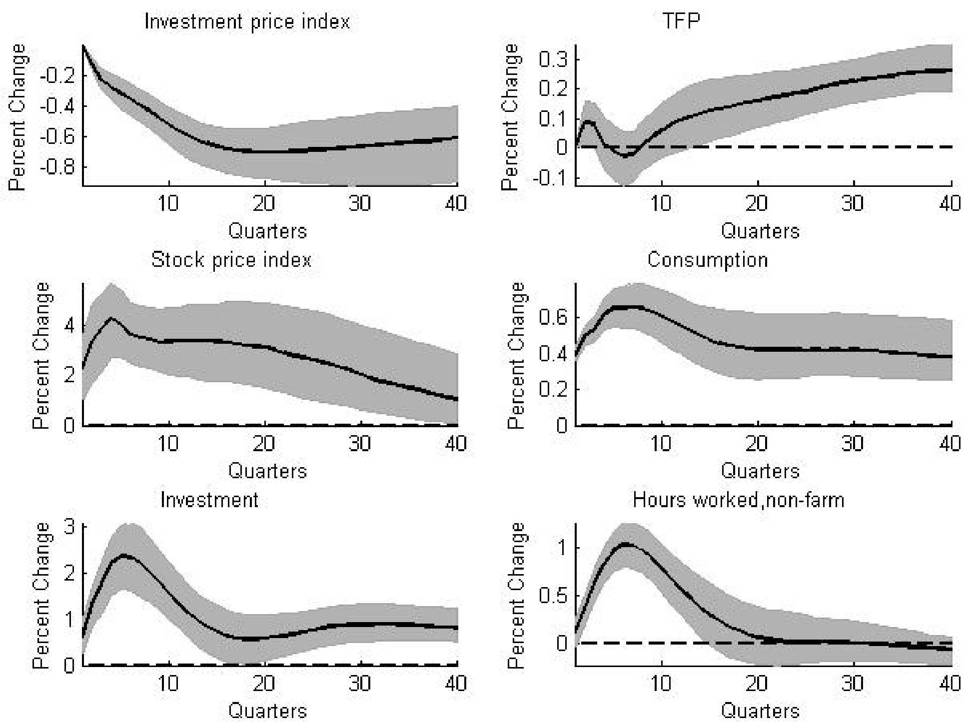
The results of this identification approach are presented in Figures (3.5) through (3.8). Let's consider the IST news shock. The stock price index, consumption, investment, and hours worked respond positively on impact to the IST news shock. The comovement of the macro variables ap-

[7]Note that when I refer to the FEV at horizon k, I mean the $(k+1)$-step-ahead FEV. For example, FEV at $k = 0$ refers to the one-quarter ahead FEV.

pears to be consistent with that observed in the case of the anticipated investment shock. A look at the dynamics of the investment price index and TFP to the IST news shock illustrates responses that are very similar to those obtained from the anticipated investment shock. For instance, TFP does not respond initially to the IST news shock, but instead gradually increases and settles at a higher and permanent level. The same dynamics are observed with the investment price index with a slow and permanent decline rather than an increase. Furthermore, in Figure (3.7), the share of the FEV of TFP, consumption, investment, and hours worked that is attributable to the IST news shock is quite identical to their counterparts from the anticipated investment shock. In other words, the IST news shock accounts for 50 percent of the FEV of the macro variables and 25 percent of the FEV of TFP. Similar responses are obtained when I apply the FMJR approach. These findings seem to suggest that the identified investment shock is in fact news about investment-specific technology. In the case of the TFP news shock, the results in Figure (3.6) tell a different story. The stock price index, consumption, and investment increase on impact to the TFP news shock while hours worked declines. The initial decline of hours worked caused by the TFP news shock, although insignificant, casts some doubt as to the interpretation that the optimism shock is a TFP news shock. In fact, the news shock accounts for a sizable portion of the FEV of macro variables, as depicted in Figure(3.8), while the optimism shock does not. In addition, the correlation between the two shocks is quite small—about 0.34. When the FMJR approach is applied, the impact response of hours to the TFP news shock is reversed from negative to positive; however, this only adds complications to the difficult task of establishing the hypothesis that the optimism shock might be a TFP news shock. See the impulse responses of the variables for the FMJR approach in Figure (3.9).

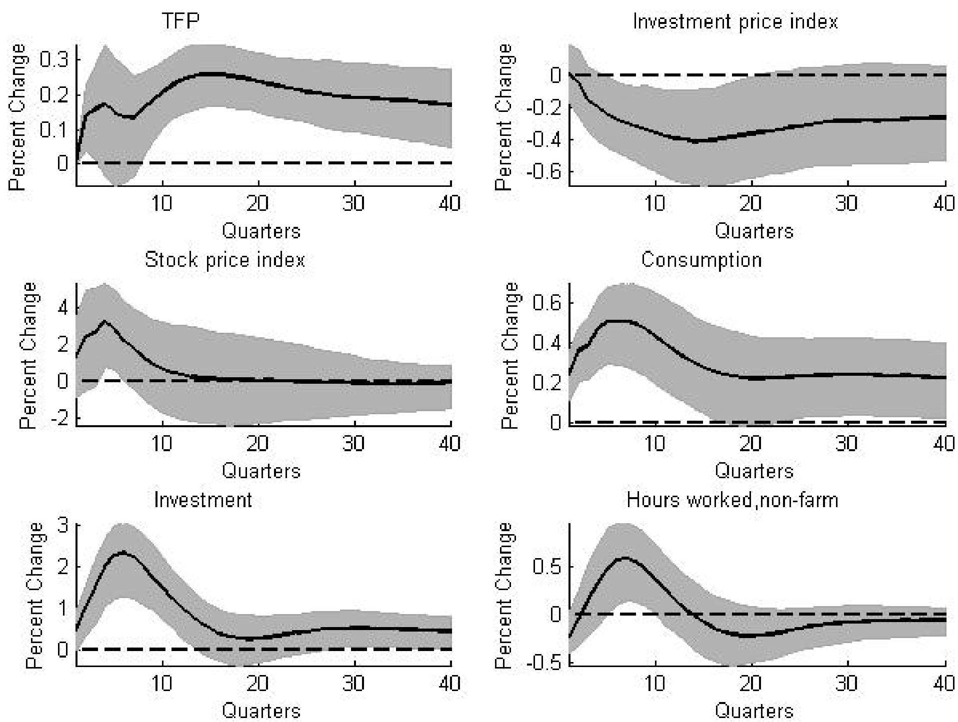
In sum, the notion that mood swings, identified as the optimism shock, are a reflection of anticipated movements in TFP and are significant factors in accounting for business cycle fluctuations appears less plausible. The optimism shock does not generate the comovement observed

Figure 3.5: Impulse Responses to a 1 percent innovation in the IST news shock



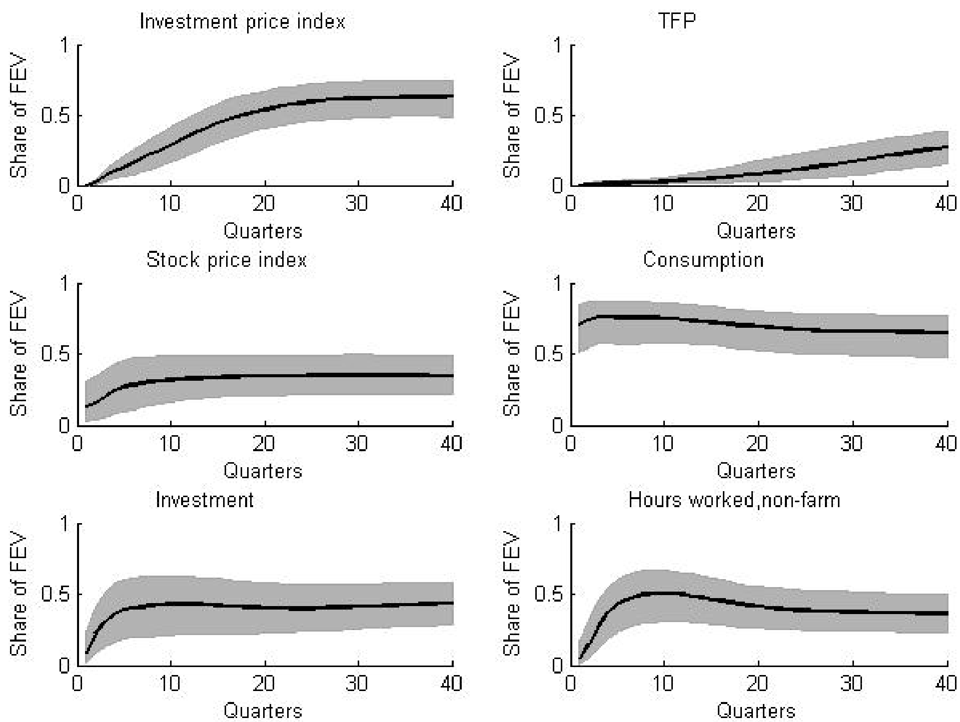
Notes: The solid line represents the median response of the variables, while the shaded gray region represents the 16^{th} and 84^{th} percentile coverage from the empirical distribution of impulse responses.

Figure 3.6: Impulse Responses to a 1 percent innovation in the TFP news shock



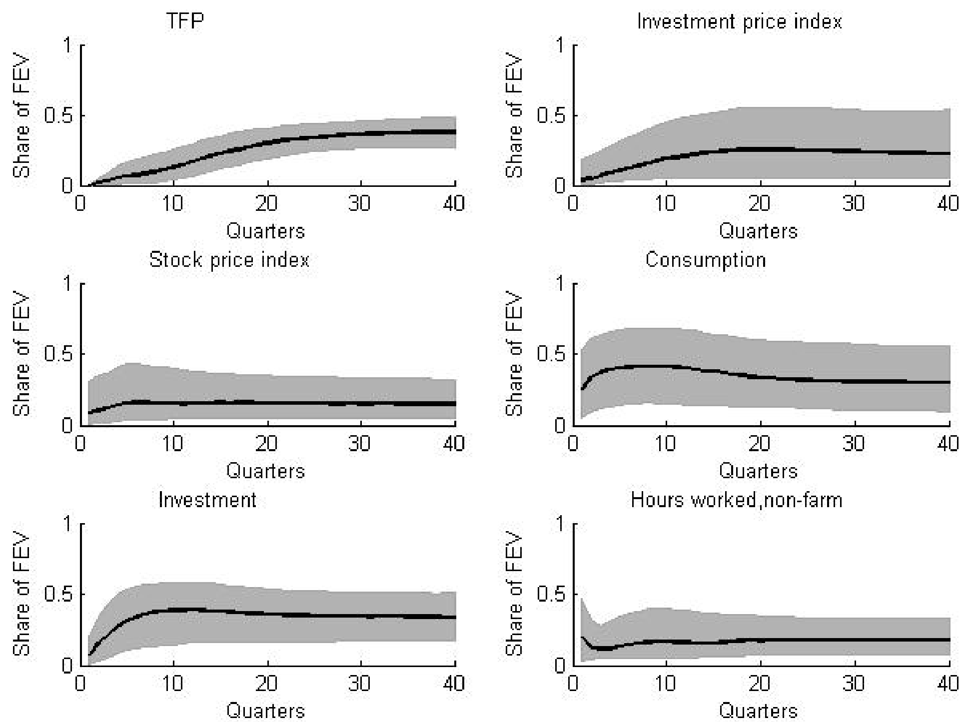
Notes: The solid line represents the median response of the variables, while the shaded gray region represents the 16^{th} and 84^{th} percentile coverage from the empirical distribution of impulse responses.

Figure 3.7: Share of the Forecast Error Variance to a 1 percent innovation in the IST news shock



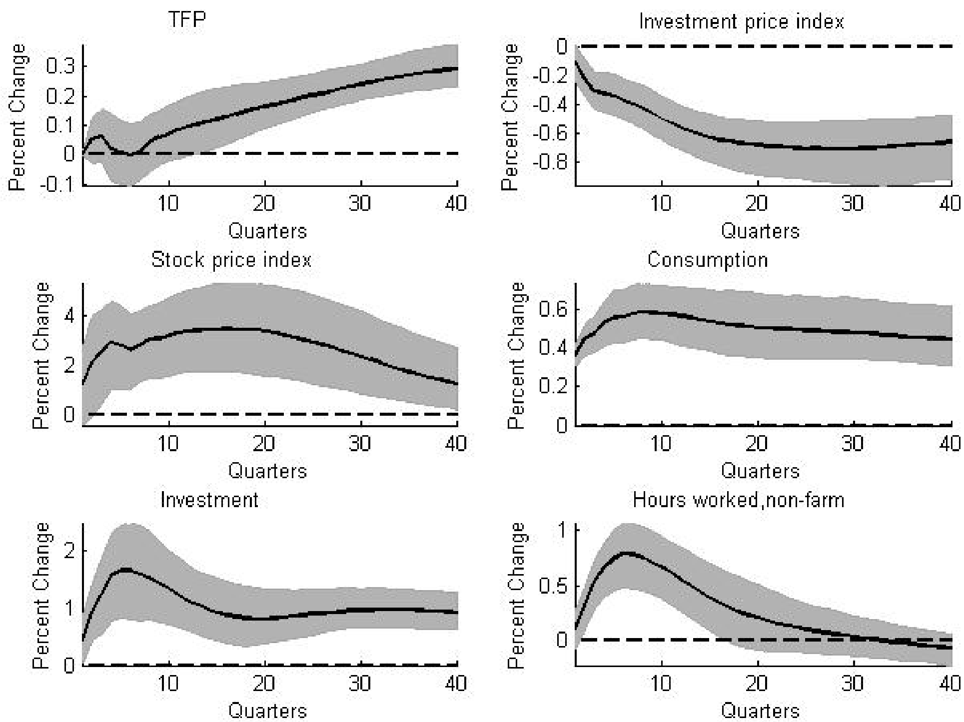
Notes: The solid line represents the median share of the FEV of the variables, while the dashed lines represent the 16^{th} and 84^{th} percentile coverage from the empirical distribution of FEVs.

Figure 3.8: Share of the Forecast Error Variance to a 1 percent innovation in the TFP news shock



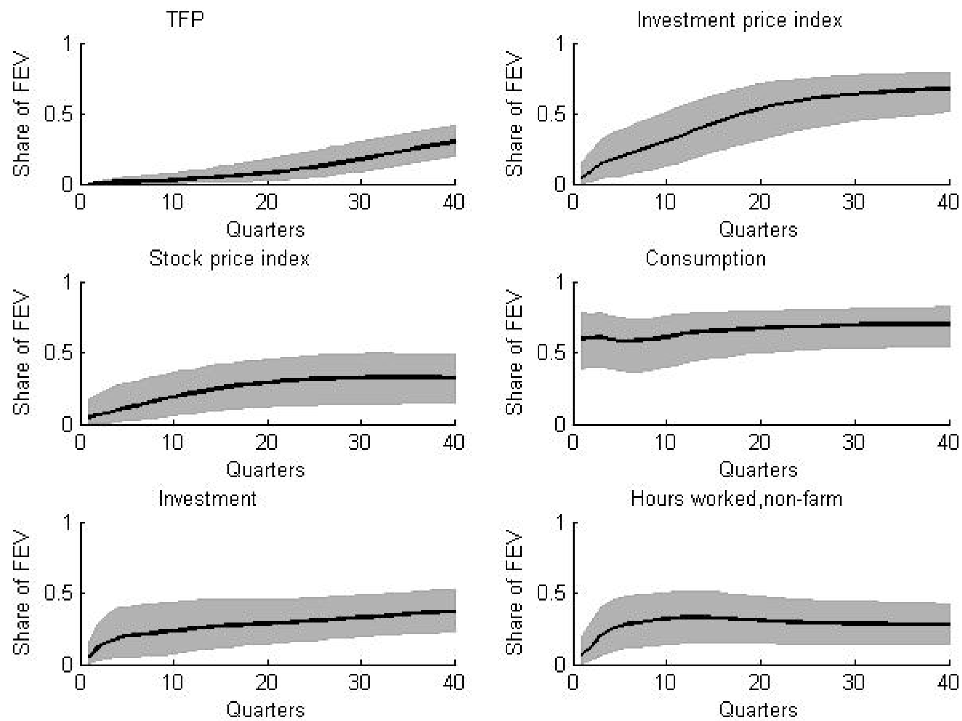
Notes: The solid line represents the median share of the FEV of the variables, while the shaded gray region represents the 16^{th} and 84^{th} percentile of the empirical distribution of FEVs.

Figure 3.9: Impulse Responses to a 1 percent innovation in the TFP news shock—FMJR approach



Notes: The solid line represents the median response of the variables, while the shaded gray region represents the 16^{th} and 84^{th} percentile coverage from the empirical distribution of impulse responses when the FMJR approach is applied.

Figure 3.10: Share of the Forecast Error Variance to a 1 percent innovation in the TFP news shock—FMJR approach



Notes: The solid line represents the median share of the FEV of the variables, while the shaded gray region represents the 16^{th} and 84^{th} percentile coverage from the empirical distribution of FEVs when the FMJR approach is applied.

among macro variables; it only accounts for a minimal fraction of the FEV of the variables. On the other hand, the anticipated investment shock appears to capture anticipated movements in technology that are embodied in capital. Yet, at the end of the day, the TFP news shock identified via the FMJR approach generates comovement in and explains a sizable portion of the FEV in macro variables as seen in Figure (3.10). Also, the TFP news shock induces a slow and permanent response and plays a role in explaining fluctuations in the investment price index. These observations raise some questions in regards to the nature and source of the TFP news shock. To investigate this, I explore the correlation between the IST news shock and the TFP news shock since they induce similar dynamics to the variables of the system. It turns out that both shocks are highly correlated—the correlation coefficient is 0.97. This seems to suggest that the two shocks might be driven by a common factor. This argument is emphasized in a concurrent paper by Chen and Wemy (2014), who argue that the close correlation between the TFP news shock and the IST news shock is a consequence of spillover effects arising from slowly diffusing innovations in investment-specific technology (IST) to TFP. This line of argument is consistent with the argument that embodied technological progress is a General Purpose Technology (GPT); that is, a new invention that leads to fundamental changes in the production process of industries using it.

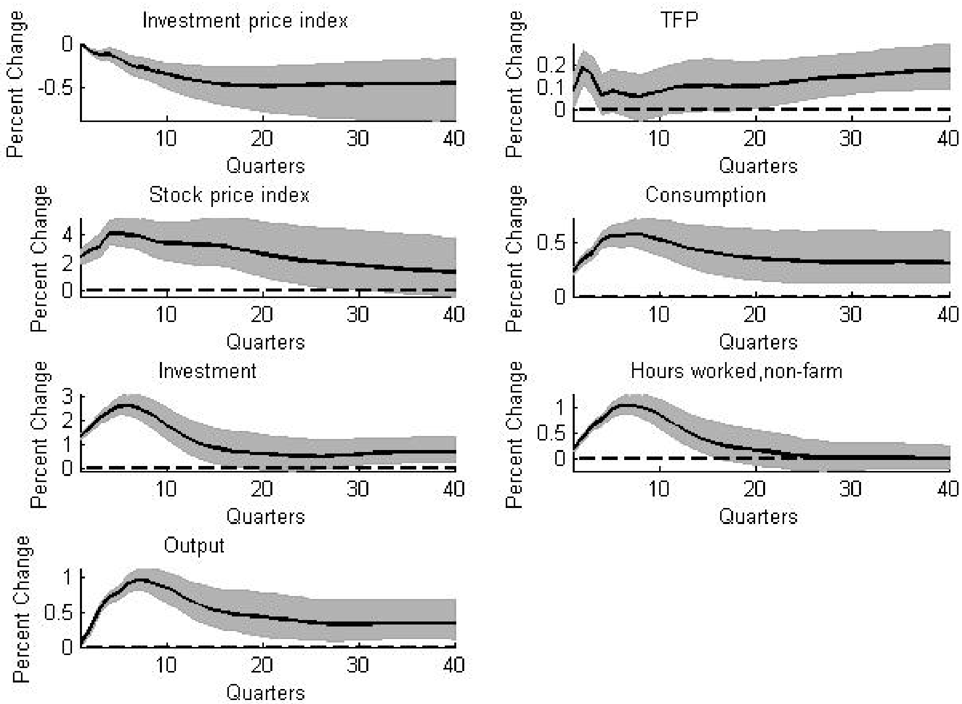
Robustness Analysis

In this section, I conduct robustness checks to verify that the results are not sensitive to: 1) A larger system of variables; 2) An alternative measure of the relative price of investment; and 2) A more restricted specification where the response of the real interest rate to the optimism shock is restricted to be non-negative on impact. To that end, I add output—measured as per capita GDP—to the set of variables. I also use the GCV quality-adjusted investment deflator.

I perform the same exercises as in Section (3.2) and Section (3.3). The results appear in

Figures (3.11) through (3.20) and they indicate that the responses of the variables are unchanged.[8] Thus, to summarize, the main findings of the paper are robust to the larger specification, the alternative measure of investment deflators, and the more restrictive specification.

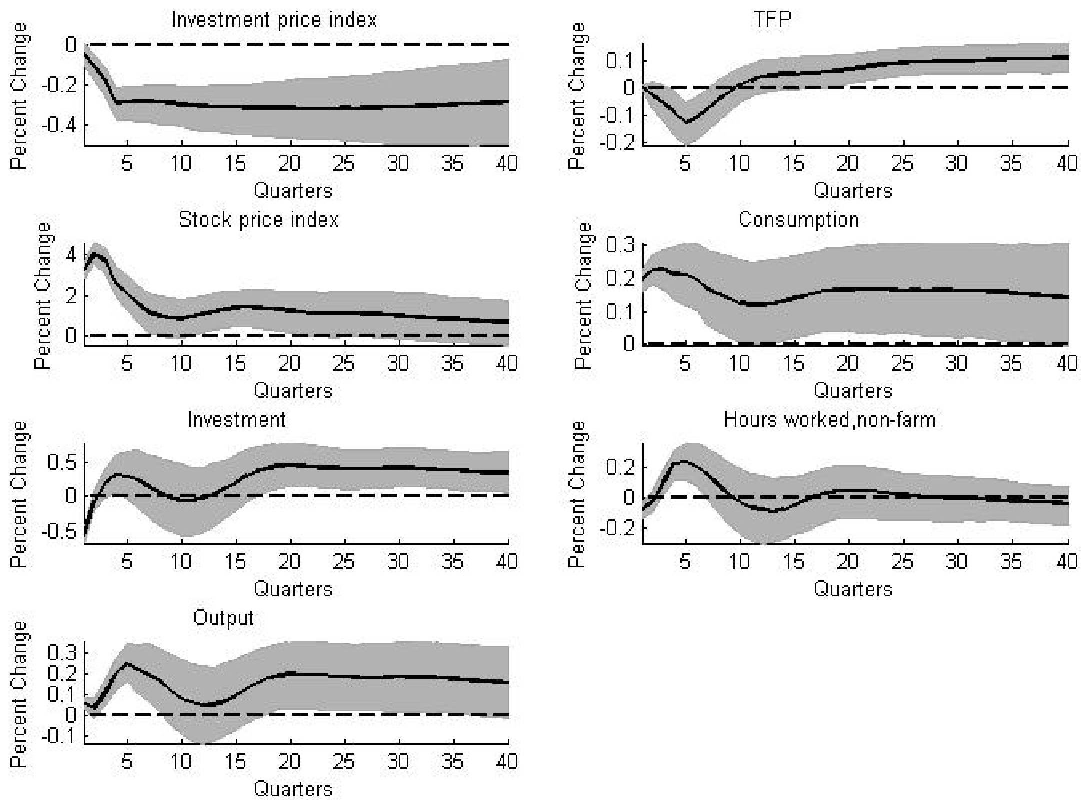
Figure 3.11: Impulse Responses to a 1 percent innovation in the anticipated investment shock—larger specification



Notes: The solid line represents the median response of the variables, while the shaded gray region represents the 16^{th} and 84^{th} percentile coverage from the empirical distribution of impulse responses in the larger specification.

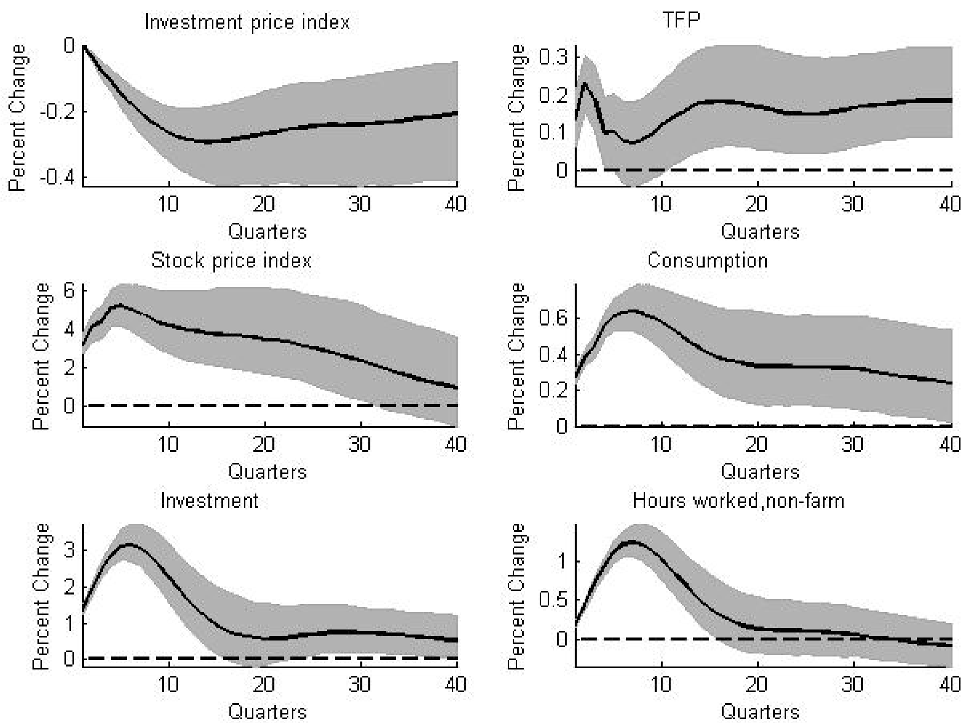
[8]The response of output to the optimism shock is positive, while investment and hours worked still respond negatively on impact. This seems to be quite odd, but it does not alter the argument that the optimism shock does not reflect permanent changes in technology and it does not serve as a plausible source of business cycles.

Figure 3.12: Impulse Responses to a 1 percent innovation in the optimism shock—the larger specification



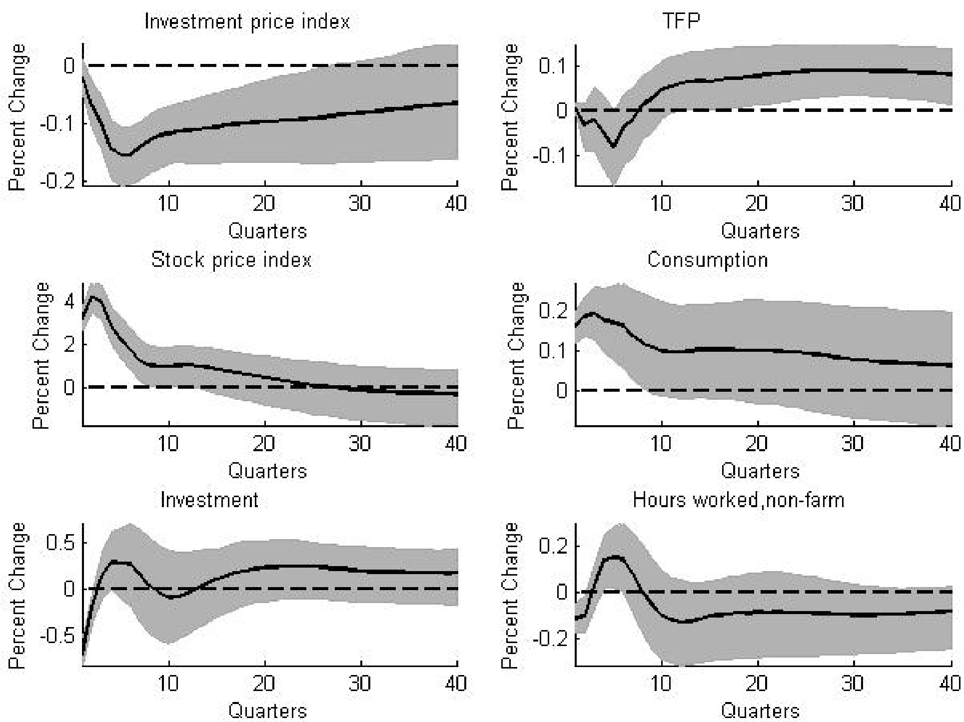
Notes: The solid line represents the median response of the variables, while the shaded gray region represents the 16^{th} and 84^{th} percentile coverage from the empirical distribution of impulse responses in the larger specification.

Figure 3.13: Impulse Responses to a 1 percent innovation in the anticipated investment shock—GCV deflator



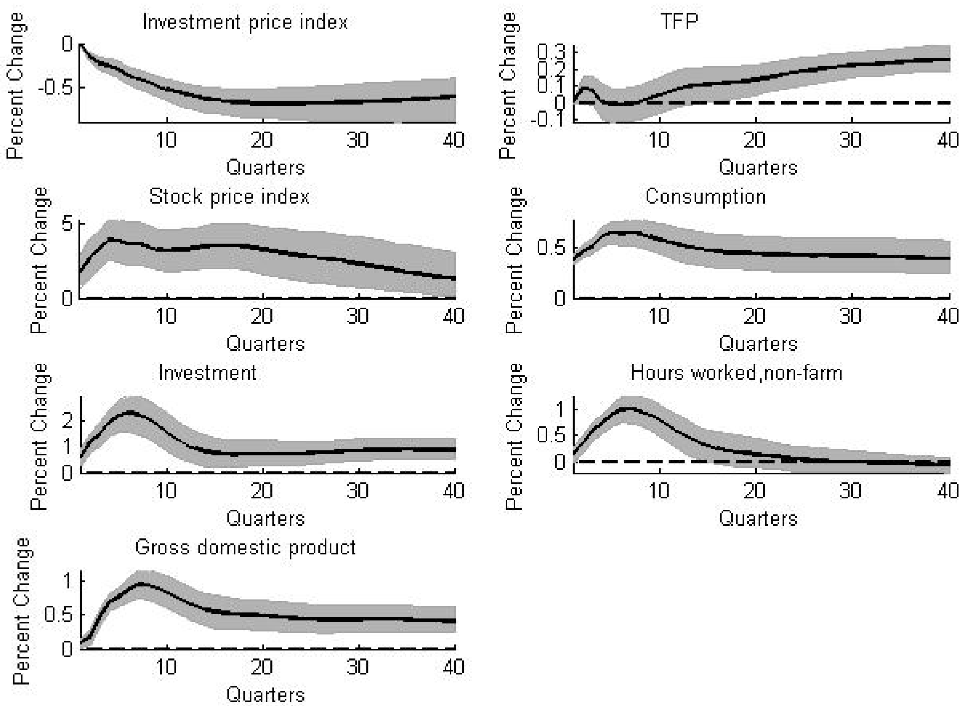
Notes: The solid line represents the median response of the variables, while the shaded gray region represents the 16^{th} and 84^{th} percentile coverage from the empirical distribution of impulse responses when the GCV deflator is used in place of the NIPA deflator.

Figure 3.14: Impulse Responses to a 1 percent innovation in the optimism shock—GCV deflator



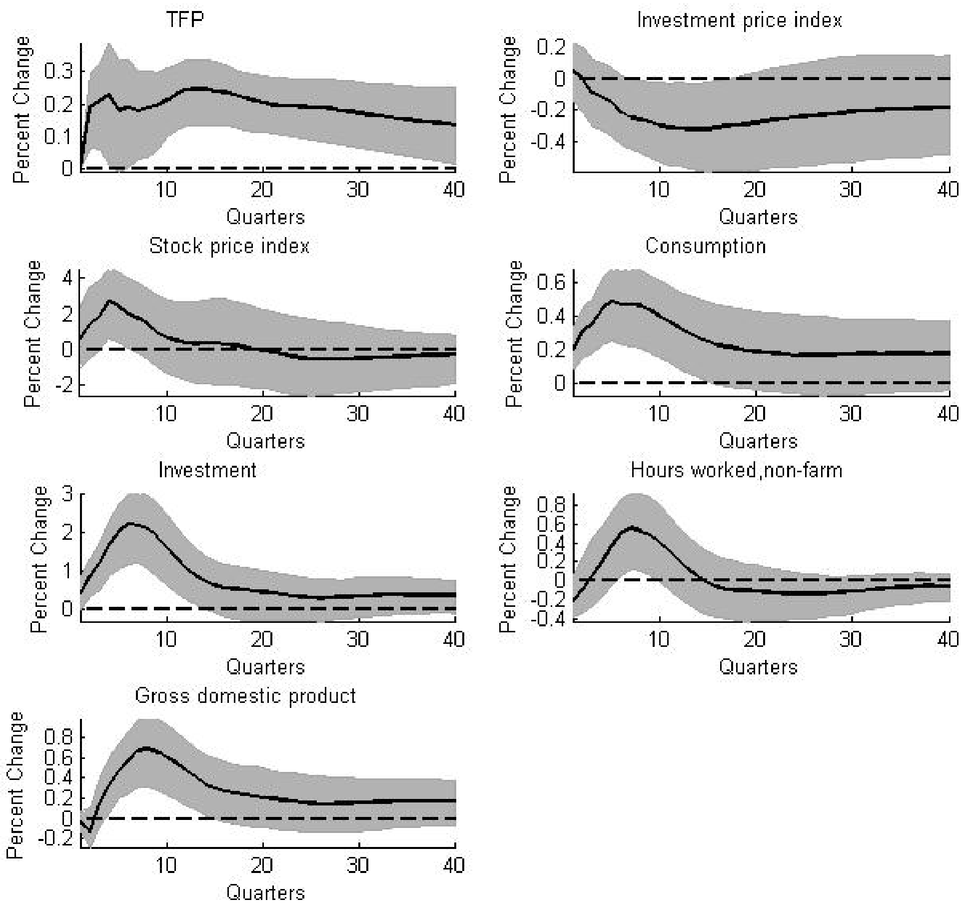
Notes: The solid line represents the median response of the variables while the shaded gray region represents the 16^{th} and 84^{th} percentile coverage from the empirical distribution of impulse responses when the NIPA deflator is replaced with the GCV deflator.

Figure 3.15: Impulse Responses to a 1 percent innovation in the IST news shock—larger specification



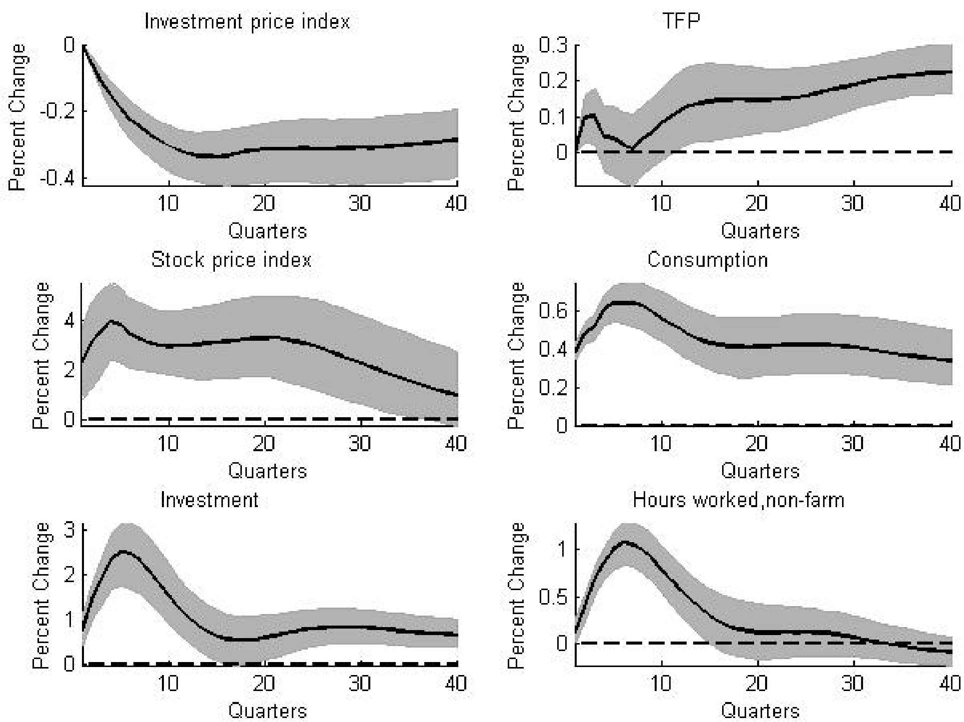
Notes: The solid line represents the median response of the variables, while the shaded gray region represents the 16^{th} and 84^{th} percentile coverage from the empirical distribution of impulse responses in the larger specification.

Figure 3.16: Impulse Responses to a 1 percent innovation in the TFP news shock—larger specification



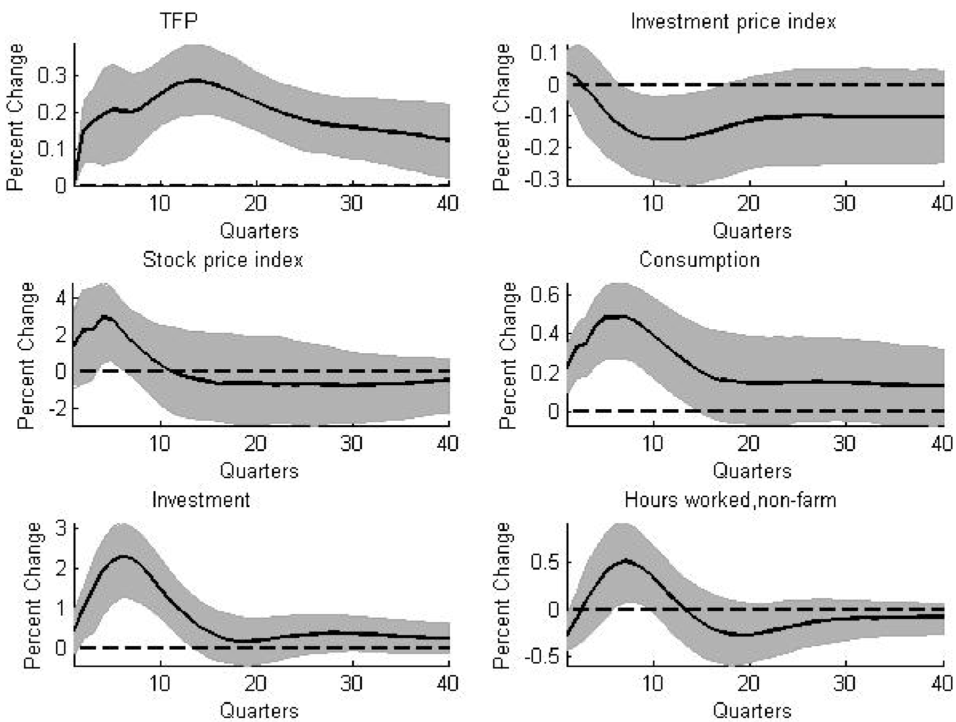
Notes: The solid line represents the median response of the variables, while the shaded gray region represents the 16^{th} and 84^{th} percentile response of the empirical distribution of impulse responses in the larger specification.

Figure 3.17: Impulse Responses to a 1 percent innovation in the IST news shock—GCV deflator



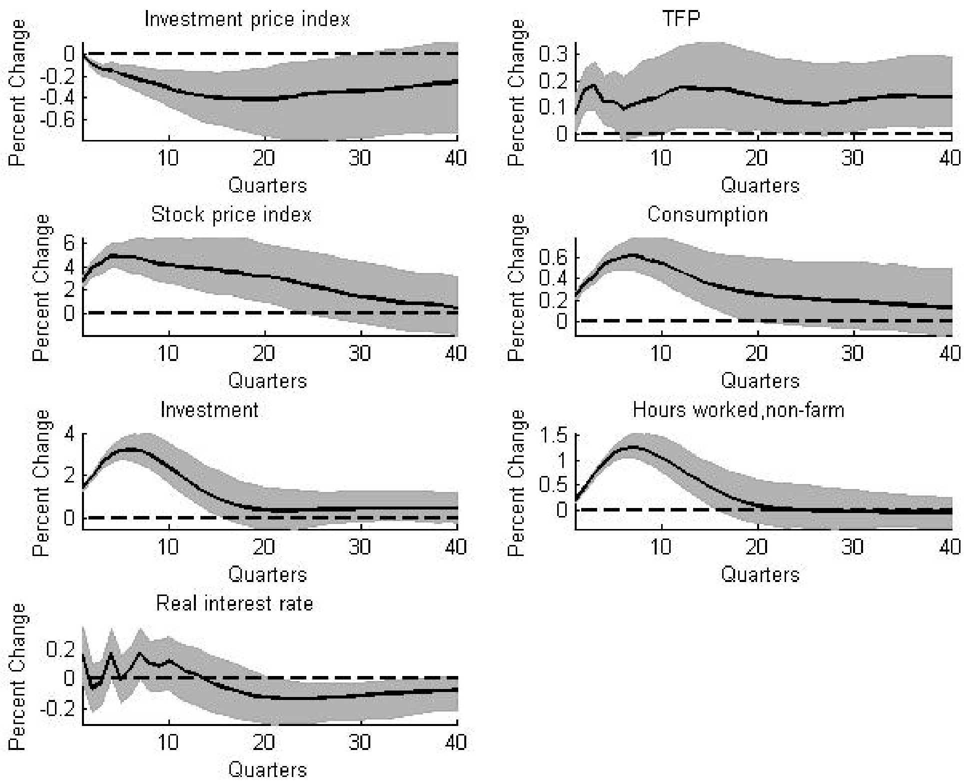
Notes: The solid line represents the median response of the variables, while the shaded gray region represents the 16^{th} and 84^{th} percentile coverage from the empirical distribution of impulse responses when the NIPA deflator is replaced with the GCV deflator.

Figure 3.18: Impulse Responses to a 1 percent innovation in the TFP news shock—GCV deflator



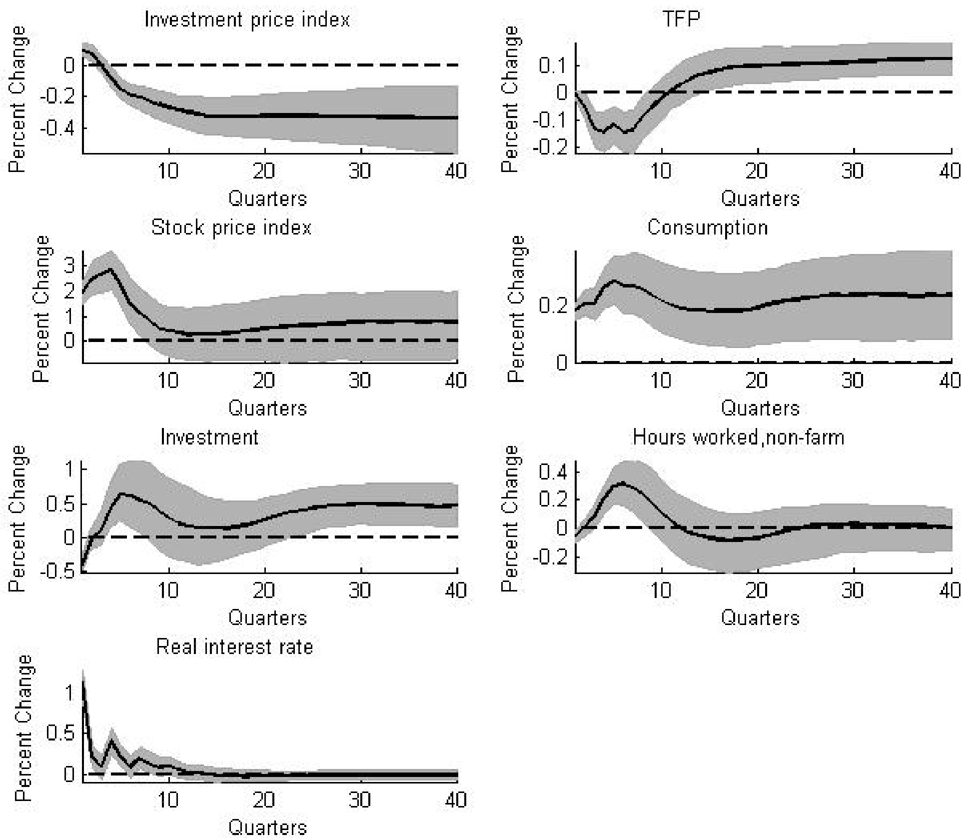
Notes: The solid line represents the median response of the variables, while the shaded gray region represents the 16^{th} and 84^{th} percentile coverage from the empirical distribution of impulse responses when the NIPA deflator is replaced with the GCV deflator.

Figure 3.19: Impulse Responses to a 1 percent innovation in the anticipated investment shock—additional restriction



Notes: The solid line represents the median response of the variables, while the shaded gray region represents the 16^{th} and 84^{th} percentile response of the empirical distribution of impulse responses in the case where the response of the real interest rate to the optimism shock is also restricted to be non-negative on impact.

Figure 3.20: Impulse Responses to a 1 percent innovation in the optimism shock—additional restriction



Notes: The solid line represents the median response of the variables, while the shaded gray region represents the 16^{th} and 84^{th} percentile response of the empirical distribution of impulse responses in the case where the response of the real interest rate to the optimism shock is also restricted to be non-negative on impact.

Conclusion

In this paper, I am particularly interested in determining whether mood swings, captured by an optimism shock, are associated with anticipated permanent changes in technology and whether they are a source of macroeconomic fluctuations as suggested by Beaudry, Nam and Wang (2011). To this end, I use a combination of sign and zero restrictions to identify simultaneously innovations in optimism and anticipated innovations in investment. The results using post-war U.S. data indicate that anticipated innovations in investment are important sources of fluctuations as they generate comovement in output, consumption, investment, and hours worked. On the other hand, innovations in optimism induce a negative response in investment and hours worked. In addition, the innovations in investment account for over 40 percent of the forecast errors of the relative price of investment, hours worked, output, investment, and consumption over a horizon of three to five years while the innovations in optimism play a minor role.

To explore the source of each innovation, I then examine the link between the two shocks and major changes in total factor productivity and the relative price of investment goods. Specifically, using the maximum forecast error variance approach, I sequentially isolate a TFP news shock and an IST news shock and I find that there is a close link between the IST news shock and the anticipated innovations in investment. Interestingly, the equivalence between the optimism shock and the TFP news shock documented by Beaudry, Nam and Wang (2011) vanishes and the optimism shock stops accounting for the FEV of TFP. The anticipated investment shock, which is established to be an IST news shock, emerges as the potential source of business cycle fluctuations.

Furthermore, when the maximum forecast horizon is applied specifically at a long but finite forecast horizon, the TFP news shock generates comovement among macro variables, explains a sizable portion of the FEV in macro variables, induces a slow and permanent response in both

TFP and the investment price index, and plays a role in explaining fluctuations in the investment price index. Additional investigation reveals that the IST news shock and the TFP news are highly correlated—the correlation coefficient is 0.97. This close relationship suggests that the two shocks might be driven by a common factor and may be the result of spillover effects arising from slowly diffusing innovations in investment-specific technology to TFP. This line of argument is consistent with the argument that embodied technological progress is a General Purpose Technology.

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