Investment-Specific Technical Changes: The Source of Anticipated TFP Fluctuations*

Kaiji Chen[†] Edouard Wemy[‡]

October 22, 2014

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 variable. 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.

Keywords: Investment-specific Technical Change; News Shocks; TFP; General Purpose Technology.

JEL Codes: E22, E32, O47.

*We would like to thank the editor and three anomymous referees for their comment. We also thank Toni Braun, André Kurmann, Deokwoo Nam, Christopher Otrok, Michael Owyang, Gian Luca Violante, Jian Wang, Zhiwei Xu, and seminar participants of the Atlanta Fed, 2014 Midwest Macro Meetings, and the 2014 Summer Meetings of North American Econometric Society for helpful discussion and comments.

[†]Corresponding Author. Emory University, Department of Economics, Atlanta, GA 30322. Email: kaiji.chen@emory.edu.

[‡]Emory University, Department of Economics, Atlanta, GA 30322. Email: ewemy@emory.edu.

1 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.[1] 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?[2] 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): a news shock to TFP and a news shock 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 variable, 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 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.

[1] 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.

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

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.[3] 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 contain 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 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 of 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

[3] 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.

horizon.

Our paper contributes to the VAR-based literature on news shocks from several perspectives.[4] 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 shock to TFP with the news shock to neutral technology.[5] Recent studies on news shocks to TFP have incorporated shock to the relative price of investment into a SVAR, but most of them assume that the shocks to the relative price of investment and the TFP news shock are orthogonal to each other.[6] 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 (2012), the TFP news shock identified under the MFEV approach is highly correlated with the optimism shock 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 the news shock to

[4]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 (2012), Ben Zeev and Kahn (2013), Otrok and Kurmann (2013), and Kurmann and Merten (2014).

[5]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.

[6]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.

aggregate TFP are almost identical to the news shock to 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 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.[7] The crucial role of news on future IST improvements in anticipated TFP fluctuations suggests that one potentially important channel for the IST news shock 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 the IST news shock 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 improvements 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, Samuels, 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,

[7] 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.

several papers study the implications of technical diffusion in business cycles.[8] However, most studies in this literature consider only unanticipated technical diffusions.[9] 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.[10] 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.

2 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's (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.[11] 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

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

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

[10] 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.

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

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.

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 innovations and structural shocks

$$\mathbf{u}_t = A\boldsymbol{\varepsilon}_t.$$

The key restriction on A is that it satisfies $\Sigma = E[A\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t' A'] = AA'$. 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 $\widetilde{\boldsymbol{\varepsilon}}_t$, $u_t = \widetilde{A}\widetilde{\boldsymbol{\varepsilon}}_t$. 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 $[\underline{k}, \overline{k}]$, 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 $[\underline{k}, \overline{k}]$. Specifically, we solve the following maximizing problem, given the Cholesky decomposition of Σ, $\tilde{A}$:

$$q_1 = argmax \;\; q_1' S q_1 \equiv q_1' [\sum_{k=\underline{k}}^{\overline{k}} \sum_{l=0}^{k} \tilde{A}' C_l' (e_i e_i') C_l \tilde{A}] q_1 \tag{1}$$

subject to

$$
\begin{aligned}
q_1' q_1 &= 1 \qquad (2)\\
q_1^{(1)} &= 0, \qquad (3)
\end{aligned}
$$

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 $k \in \left[\underline{k}, \overline{k}\right]$.[12] 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.

3 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 sectoral 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 competitive 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

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

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 sectoral TFP is equivalent to the sectoral 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:

$$\log TFP_t^I/TFP_t^C = \log P_t^C/P_t^I \equiv \log PC_t, \tag{4}$$

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 (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 7.1, 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.[13] 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.[14]

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

[14] 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

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:

$$\log PC_t = \log \Phi_t + \varpi_t + \omega_t. \tag{5}$$

In equation (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.[15] Equation (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.

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.[16] In Appendix 7.2, 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.[17]

$$\Delta \log TFP_t = \left(1 - w^I\right) \Delta \log TFP^C_t + w^I \Delta \log TFP^I_t, \tag{6}$$

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

$$\Delta \log TFP_t = \Delta \log TFP^C_t + w^I \Delta \log \Phi_t. \tag{7}$$

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.

[15] Adding the unanticipated permanent non-IST shocks to PC in equation (5) would not affect our interpretation of the news shocks to PC, since we impose zero impact restriction in our empirical identification.

[16] 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.

[17] 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.

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.[18] Since equation (7) holds for all period t, it implies that

$$\log TFP_t = \log TFP_t^C + w^I \log \Phi_t. \tag{8}$$

According to (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 (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.[19]

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.[20] 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 permanents shocks to either Φ_t or TFP_t^C.

3.1 IST Diffusion and Spillover

Consider a specification where innovations to IST involve a diffusion process that does not immediately increase productivity.[21] 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

[18] 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.

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

[20] 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.

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

consumption sector:

$$\log \Phi_t = \sum_{i=0}^{\infty} d_i^I \eta_{1,t-i}^I + \nu_t^I, \tag{9}$$

$$\log TFP_t^C = \sum_{i=0}^{\infty} d_i^N \eta_{1,t-i}^N + \nu_t^N + \alpha \sum_{i=0}^{\infty} d_i^I \eta_{1,t-i}^I, \tag{10}$$

$$d_i^J = 1 - (\delta_J)^i, 0 \leq \delta_J < 1, \; J = I \text{ or } N, \tag{11}$$

$$\nu_t^J = \rho^J \nu_{t-1}^J + \eta_{2,t}^J, \; 0 \leq \rho^J < 1, \; J = I \text{ or } N, \tag{12}$$

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 $\eta_2^N \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{\eta_2^N}\right)$.[22] By construction, all primitive shocks are orthogonal to each other.[23]

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 a temporary IST shock. 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.[24] Specifically, given the diffusion process, the value of α captures the

[22] Leeper and Walker (2011) argue that news shocks containing moving-average (MA) components, as in (9), are better in line with slow technology diffusion than i.i.d. news shocks drawn from distinct probability distributions.

[23] 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.

[24] Note that equation (10) implicitly assumes that non-IST permanent shocks to PC, v_{1t}, are orthogonal

elasticity of TFP^C with respect to the IST news shock η_1^I in the long run.[25] 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 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, Van 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.[26]

We now express TFP in terms of primitive shocks. Plugging equation (9) and (10) into (8), we can rewrite aggregate TFP as

$$\log TFP_t = \sum_{i=0}^{\infty} d_i^N \eta_{1,t-i}^N + \beta \sum_{i=0}^{\infty} d_i^I \eta_{1,t-i}^I + \nu_t, \tag{13}$$

where $\beta \equiv \alpha + w^I$ captures the overall effects of the IST news shock 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.[27]

$$\log TFP_t = \sum_{i=1}^{\infty} d_i \eta_{1,t-i} + \nu_t. \tag{14}$$

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

to consumption-sector TFP. In Appendix 7.4, 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.

[25] 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.

[26] 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.

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

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 horizons. Equation (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 the 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 $\Omega_{TFP,\eta_{1,t}^I}(k)$.

$$\Omega_{TFP,\eta_1^I}(k) = \frac{\beta^2 \sigma_{\eta_1^I}^2 \sum_{j=0}^{k-1} (d_j^I)^2}{\Omega_{TFP}(k)}, \tag{15}$$

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 $\beta^2\sigma_{\eta_1^I}^2$, the larger is the share of the forecast error variance of TFP attributable to η_1^I at all horizons except for the impact period. Intuitively, the contribution of the IST news shock to overall TFP fluctuations depends on both their internal propagation, captured by β, and their magnitude, captured by $\sigma_{\eta_1^I}^2$. Appendix 7.3 shows that if $k \to \infty$, equation (15) becomes

$$\Omega_{TFP,\eta_1^I}(k) = \frac{1}{1 + \sigma_{\eta_1^N}^2 / \left(\beta^2 \sigma_{\eta_1^I}^2\right)}. \tag{16}$$

Equation (16) shows that, in the long run, the share of the FEV of TFP attributable to the IST news shock depends positively on $\beta^2\sigma_{\eta_1^I}^2/\sigma_{\eta_1^N}^2$, 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 (5) with equation (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

$$\Omega_{PC,\eta_1^I}(k) = \frac{\sigma_{\eta_1^I}^2 \sum_{j=0}^{k-1} (d_j^I)^2}{\Omega_{PC}(k)}, \tag{17}$$

where $\Omega_{PC}(k)$ denotes the FEV of PC k-step ahead. Appendix 7.3 shows that as $k \to \infty$, equation (17) becomes

$$\Omega_{PC,\eta_1^I}(k) = \frac{1}{1 + \sigma_{\upsilon_1}^2 / \sigma_{\eta_1^I}^2}. \tag{18}$$

Equation (16) and (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 the IST news shock and υ_{1t}

$$\tilde{\varepsilon}_t^{PC} = \eta_{1t}^I + \upsilon_{1t}. \tag{19}$$

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

$$\tilde{\varepsilon}_t^{TFP} = \beta \eta_{1t}^I + \eta_{1t}^N. \tag{20}$$

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, the news shock to the inverse of the relative price of investment (PC) is not identical to the IST news shock. Nonetheless, the importance of the IST news shock for long-run fluctuations in PC can still be verified by examining the share of the FEV of PC attributable to the TFP news shock. 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 the TFP news shock in the long run, as later shown by our empirical evidence, implies that the IST news shock plays a 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 variable at $k \rightarrow \infty$ can, therefore, be expressed as follows:

$$\begin{aligned}
\rho\left(\tilde{\varepsilon}_t^{PC}, \tilde{\varepsilon}_t^{TFP}\right) &= \frac{cov\left(\tilde{\varepsilon}_t^{PC}, \tilde{\varepsilon}_t^{TFP}\right)}{\sigma_{\tilde{\varepsilon}_t^{PC}} \cdot \sigma_{\tilde{\varepsilon}_t^{TFP}}} \\
&= \frac{\beta \sigma^2_{\eta^I_{1t}}}{\sqrt{\sigma^2_{\eta^N_1} + \beta^2 \sigma^2_{\eta^I_1}} \sqrt{\sigma^2_{\eta^I_1} + \sigma^2_{\upsilon_1}}} \\
&= \frac{1}{\sqrt{1 + \sigma^2_{\eta^N_1} / \left(\beta^2 \sigma^2_{\eta^I_1}\right)} \sqrt{1 + \sigma^2_{\upsilon_1} / \sigma^2_{\eta^I_1}}}.
\end{aligned} \tag{21}$$

The right-side of equation (21) captures the product of the share of the FEVs of TFP and PC attributable to the IST news shock. 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 shock 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 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 of the common driving force underlying TFP and PC. Therefore, in Appendix 7.4, we also consider an alternative data-generating process that allows spillover in both directions.[28] We show that the corre-

[28]We thank one referee for this suggestion.

lation between the news shocks on TFP and PC would be negative if the spillover from the consumption to the investment sector dominates, and vice 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 the IST news shock or the shock 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 7.5 shows that as $k \to \infty$, β equals

$$\beta = \sqrt{\frac{\Omega_{TFP,\eta_1^I}(k) \times \sigma_{TFP}^2}{\Omega_{PC,\eta_1^I}(k) \times \sigma_{PC}^2}}, \tag{22}$$

where σ_{TFP}^2 and σ_{PC}^2 denote the variances of news shocks to TFP and PC, respectively. Therefore, with the value of w^I, the investment share in aggregate value-added, obtained from the U.S. data, we can measure the magnitude 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 the IST news shock to anticipated future TFP fluctuations.

4 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 (1990) 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.[29]

The series of aggregate TFP growth is taken from Fernald (2012), measured as the growth rate of business-sector TFP.[30] 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 the TFP series unadjusted for capital utilization.

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

$$\Delta \log TFP_t^C = \Delta \log TFP_t - w^I \Delta \log P_t^C / P_t^I, \tag{23}$$

with the values of w^I taken from Fernald (2012).[31] 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.[32] 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 added in the non-farm business sector, taken from the Bureau of Economic Analysis

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

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

[31] Note that equation (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.

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

(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 cointegration of unknown forms.[33] 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 (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 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., $\underline{k} = \overline{k} = k$.

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

5 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.

5.1 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.

5.1.1 A Six-variable System

Figure 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 the news shock 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 (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.[34] Furthermore, the positive comovement of PC and TFP in response to the news shock to PC is consistent with the spillover from the IST news shock to the consumption-sector TFP, rather than from the opposite direction.

[34] The initial negative response of aggregate TFP to the news shock 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.

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.[35] 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.[36] 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 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 shock 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. 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 the IST news shock, which spills over to consumption-sector TFP, plays 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.[37]

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

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

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

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), 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.[38] By contrast, the fluctuation of investment attributable to the news shock 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 1 summarizes the FEV coefficients of various variables attributable to the news shock on PC at different time horizons.

Figure 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 to each other. 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 the IST news shock is the main primitive shock underlying the long-run variations of both aggregate TFP and the relative price of investment.

We now quantify the relative importance of the spillover effect of the IST news shock. Our empirical findings suggest that the IST news shock dominates 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 the FEV of TFP and PC attributable to the identified news shock to PC. Since equations (16) and (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 (22) gives $\beta = 0.89$.[39] 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 effect, 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.

[38] In Section 5.2.4, we show that our main findings are robust to dropping zero restrictions, suggesting that long-run shocks to PC are largely anticipated.

[39] 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.

5.1.2 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 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, 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 IST shock would drive down both the stock price and the relative price of investment, as it increases the supply of investment goods.[40] 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 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.

[40] 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.

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

5.2 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 3. After that, we check the robustness of our results under a VECM specification. 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.

5.2.1 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 (16) and (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 the IST news shock.

Figure 6 reports the IRFs of various variables to these two news shocks with a TFP series of the consumption sector.[41] 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

[41] 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.

news shocks is 0.9807. This finding supports the spillover effect of IST as a general purpose technology in aggregate TFP fluctuations.

5.2.2 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 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.[42]

5.2.3 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 Otrok and Kurmann (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, the term spread, and other nominal variables.

5.2.4 Without Zero Restrictions

In our theoretical model, the IST news shock is 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 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 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 0.9795. This suggests that permanent innovations to

[42] 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.

investment-specific technology are indeed largely anticipated and are one of the main sources of anticipated TFP fluctuations in the long run.

5.2.5 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).[43] 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.[44] 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 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.

5.2.6 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 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.

[43] We follow Lutkepohl (2005) to incorporate stationary variables, such as hours worked, in the model.

[44] 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).

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.

5.2.7 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.[45]

The results are presented in Figure 9 where the correlation between the news shock 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).[46] Thus, we argue that the main results of the paper are not explained by these other macroeconomic shocks.

5.3 Alternative Forecast Horizons

So far, our news shocks are identified by maximizing the FEVs of the corresponding variable 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 the IST shock as general purpose technology only if the two news shocks capture the long-run fluctuations of TFP and PC.

[45] 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.

[46] 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.

Another implication of the IST diffusion process is that, given that either TFP or PC may be affected by temporary disturbances in 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 the news shocks are identified as shocks that maximize the sum of the 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 Otrok and Kurmann, 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 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 the TFP news shock 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 the TFP news shock 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 the TFP news shock on all variables, except hours worked, is around half of their counterparts for the news shock 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, the news shock to TFP accounts for much less of the fluctuations of PC than the news shock to PC (Figure 11). Also, the FEV of consumption, output, and in particular, hours worked explained by the news shock to TFP is much lower than the news shock to PC. The only exception is TFP, which fluctuations in the short and medium runs are more attributable to the TFP news shock than the news shock to PC.[47]

We generalize the above results by varying the upper bound of the forecast horizon,

[47] 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).

while maintaining the zero lower bound. The left two columns of Table 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 $\overline{k}$, 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 12 compares the IRFs to the news shock to PC under $\overline{k} = 40$ and 120. We see that the IRFs for each variable are fairly close. If any difference exists, the identified news shock under $\overline{k} = 120$ is quantitatively more important for all variables in the long run. The correlation coefficient of the identified news shock 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 the TFP news shock identified under $\overline{k} = 40$ 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, forecast horizon. The results under this approach are reported in the right two columns of Table 5. Interestingly, under this alternative approach, the correlation coefficient of the two identified news shocks is robust to the choice of forecast horizon.[48] For example, at $\underline{k} = \overline{k} = 40$, the correlation coefficient of the two identified news shocks is 0.9639. Moreover, Figure 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 the robustness of these 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 shock. This allows TFP news shocks to capture more precisely shocks that drive the long-run movement of TFP.[49] Again, the high correlation of the two empirically identified news shocks under

[48] We also compute the value of β according to equation (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.

[49] 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.

this alternative approach supports our view that the IST news shock is 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 the MFEV. All these findings support that the IST news shock as the common long-run shocks to TFP and PC is one main driver of anticipated TFP fluctuations.

6 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: a news shock to TFP and a news shock 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 variable. 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.

References

[1] Acemoglu, D., P. Aghion, C. Lelarge, J. Van Reenen, and F. Zilibotti (2007), "Technology, Information, and the Decentralization of the Firm," *Quarterly Journal of Economics*, November, 1759-1799.

[2] Andolfatto, D., and G. M. MacDonald (1998), "Technology Diffusion and Aggregate Dynamics," *Review of Economic Dynamics*, 1, 338-370.

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

[4] Basu, S., J. Fernald, and M. Kimball (2006), "Are Technology Improvements Contractionary," *American Economic Review*, 96, 1418-1448.

[5] Basu, S., J. Fernald, J. Fisher, and M. Kimball (2013), "Sector-specific Technical Changes," Working paper, Boston College.

[6] Basu, S., J. Fernald, and N. Oulton (2004), "The Case of the Missing Productivity growth, or Does Information Technology Explain Why Productivity Accelerated in the United States but Not in the United Kingdom?", *NBER Macroeconomics Annual*, V. 18.

[7] Beaudry, P., and B. Lucke (2010), "Letting Different Views about Business cycles compete," *NBER Macroeconomics Annual*, 24, 413-455.

[8] Beaudry, P., D. Nam, and J. Wang (2012), "Do Mood Swings Drive Business Cycles and is it Rational?", NBER working paper.

[9] Beaudry, P., and F. Portier (2006), "News, Stock Prices and Economic Fluctuations," *American Economic Review*, 96(4), 1293-1307.

[10] Bresnahan, T., E. Brynjolfsson, and L. M. Hitt (2002), "Information Technology, Workplace Organization and the Demand for Skill Labor: Firm Level Evidence," *Quarterly Journal of Economics*, 117(1), 339-376.

[11] Chen, K., and Z. Song (2013), "Financial Frictions on Capital Allocation: A Transmission Mechanism of TFP Fluctuations," *Journal of Monetary Economics*, Vol. 60, 683-703.

[12] Christiano, L. J., and J. D. Fisher (2003), "Stock Market and Investment Goods Prices: Implications for Macroeconomics," NBER working paper, No. 10031

[13] Christiano, L. J., and T. J. Fitzgerald (1998), "The Business Cycle: It's Still a Puzzle," Federal Reserve Bank of Chicago, *Economic Perspectives,* (22), 56-83.

[14] Comin, D. A., A. M. Santacreu, and M. Gertler (2009), "Technology Innovation and Diffusion as Sources of Output and Asset Price Fluctuations," NBER working paper, No. 15029.

[15] Commins, J., and G. L. Violante (2002), "Investment-specific Technical Change in the United States (1947–2000): Measurement and Macroeconomic Consequence," *Review of Economic Dynamics*, 5, 243-284.

[16] Fernald, J. (2012), "A Quarterly, Utilization-Adjusted Series on Total Factor Productivity," working paper, Federal Reserve Bank of San Francisco.

[17] Fisher, J. (2006), "The Dynamic Effects of Neutral and Investment-Specific Technology Shocks," *Journal of Political Economy*, 114(3), 413-451.

[18] Fisher, J. (2010), "Comment On: Letting Different Views about Business Cycles Compete," *NBER Macroeconomics Annual*, 24, 457-474.

[19] Francis, N., M. Owyang, J. Rosh, and R. DiCecio (2012), "A Flexible Finite Horizon Identification of Technology Shocks," working paper, Federal Reserve Bank of St. Louis.

[20] Francis, N. and V. Ramey (2005), "Is the Technology-driven Real Business Cycle Hypothesis Dead? Shocks and Aggregate Fluctuations Revisited," *Journal of Monetary Economics*, 52, 1379-99.

[21] Gilchrist, S., and E. Zakrajšek (2012), "Credit Spread and Business Cycle Fluctuations," *American Economic Review*, 102 (4), 1692-1720.

[22] Gordon, Robert J. (1990), The Measurement of Durable Goods Prices. Chicago: University of Chicago Press.

[23] Greenwood, J., Z. Hercowitz, and P. Krusell (1997), "Long-run Implications of Investment-specific Technological Changes," *American Economic Review*, 87, 342-362.

[24] Grubler, A. (1991), "Diffusion: Long Term Patterns and Discontinuities," *Technological Forecasting and Social Change*, 39, 159-80.

[25] Guerrieri, L., D. Henderson, and J. Kim (2010), "Interpreting Investment-specific Technology Shocks," Federal Reserve Board, Discussion Paper, No. 1000.

[26] Jaimovich, N., and S. Rebelo (2009), "Can News about the Future Drive the Business Cycle", *American Economic Review*, 99, 1097-1118.

[27] Jorgenson, D. W., M. Ho, J. Samuel, and K.J. Stiroh (2007), "Industry Origins of the U.S. Productivity Resurgence," *Economic System Research*, September, 19 (3): 229-52.

[28] Jovanovic, B., and S. Lach (1997), "Product Innovation and the Business Cycle," *International Economic Review*, 38 (1), 3-22.

[29] Justiniano, A., G. Primiceri, and A. Tambalotti (2011), "Investment Shocks and the Relative Price of Investment," *Review of Economic Dynamics*, 14(1), January, 101-121.

[30] Kilian, L. (1998), "Small-sample Confidence Intervals for Impulse Response Functions," *Review of Economics and Statistics*, 80(2), 218-230.

[31] Kilian, L. (2008), "Endogenous Oil Supply Shocks: How Big are They and How Much Do they Matter for the U.S. Economy," *Review of Economics and Statistics*, 90(2), 216-240.

[32] Kurmann, A. and E. Merten (2014), "Stock Prices, News and Economic Fluctuations: Comment", *American Economic Review*, 104 (4), 1439-1450.

[33] Leeper, E., and T. Walker (2011), "Information Flows and News Driven Business Cycles," *Review of Economic Dynamics*, 14 (1), 55-71.

[34] Lippi, M., and L. Reichlin (1994), "Diffusion of Technical Change and the Decomposition of Output into Trend and Cycle," *Review of Economic Studies*, 61, 19-30.

[35] Lutkepohl, H. (2005), *New Introduction to Multiple Time Series Analysis*, Springer-Verlag, Berlin.

[36] Nam, D., and J. Wang (2014), "Are Predictable Improvements in TFP Contractionary or Expansionary: Implications from sectoral TFP," Working paper, Federal Reserve Bank of Dallas.

[37] Otrok, C., and A. Kurmann (2013), "News Shocks and the Term Structure of Interest Rates," *American Economic Review*, 103 (6), 2012-2032.

[38] Romer, C. and D. Romer (2004), "A New Measure of Monetary Shocks," *American Economic Reivew*, 94 (4), 1055-1084.

[39] Romer, C., and D. Romer (2010), "The Macroeconomic Effect of Tax Changes: Estimates Based on a New Measure of Fiscal Shocks," *American Economic Reivew*, 100, 763-801.

[40] Rotemberg, J. J. (2003), "Stochastic Technical Progress, Smooth Trends, and Nearly Distinct Business Cycles," *American Economic Review*, 93(5), 1543-1559.

[41] Schmitt-Grohé, S. (2010), "Comment on: Letting Different Views about Business Cycles Compete," *NBER Macroeconomics Annual*, 24, 475-489.

[42] Schmitt-Grohé, S. and M. Uribe (2011), "Business Cycle with a Common Trend in Neutral and Investment-specific Productivity," *Review of Economic Dynamics*, 14, 122-135.

[43] Schmitt-Grohé, S. and M. Uribe (2012), "What's News in Business Cycles?" *Econometrica*, 80(6), 2733-2764.

[44] Uhlig, H. (2003), "What Moves Real GNP?", Unpublished manuscript.

[45] Valentinyi, Á. and B. Herrendorf (2008), "Measuring factor income shares at the sectoral level," *Review of Economic Dynamics,* 11, 820-835.

[46] Ben Zeev, N. and H. Khan (2013), "Investment-Specific News Shocks and U.S. Business Cycles," Working paper, Carleton University.

7 Appendix: Not for publication

In this appendix, we first derive the relationship between the relative price of investment and the relative TFP of the investment sector in a generalized two-sector model. We then derive the decomposition of changes in aggregate TFP. Next, we analytically derive the contribution of IST innovations to the forecast error variance of TFP and the relative of price of investment in the model described in Section 3. Also, we explore the correlation of the two news shocks under the assumption that there exists spillover from consumption-specific technology to the investment-sector TFP. Finally, we derive the measure of IST spillover.

7.1 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, $i \in \{C, I\}$.[50] 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 $TFP_t^I \equiv TFP_t^C \Phi$.[51] The first-order conditions implies

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

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

[51] 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

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

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 (5).

7.2 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

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

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 (6).

7.3 Derivation of Theoretical FEV

We now derive equations (16) and (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 (12) and (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 (11) and (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

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

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

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

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

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

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

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

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

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 $\sigma_{\upsilon_1}^2/\sigma_{\eta_1^I}^2$. Therefore, as $k \to \infty$,

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

7.4 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.[52] We show that in this framework, the sign of the correlation of the two empirically identified news shocks measures the direction of spillover.

[52] 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.

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

$$\left[\begin{array}{c} \log TFP_t^C \\ \log TFP_t^I \end{array}\right] = B \left[\begin{array}{c} \epsilon_t^C \\ \epsilon_t^I \end{array}\right], \tag{A.21}$$

where

$$B = \left[\begin{array}{cc} B_{11} & B_{12} \\ B_{21} & B_{22} \end{array}\right] \tag{A.22}$$

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,

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

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

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

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:

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

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:

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

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 (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.

7.5 The Measure of IST Spillover Effects

Finally, we derive the measure of IST spillover effects. To this end, we first derive β in equation (22). As $k \to \infty$, we have

$$\sigma^2_{PC} = \sigma^2_{\eta_1^I} + \sigma^2_{\upsilon_1}, \tag{A.18}$$

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 $\sigma^2_{\eta_1^I}$ as

$$\sigma^2_{\eta_1^I} = \Omega_{PC,\eta_1^I}(k) \times \sigma^2_{PC}, \tag{A.19}$$

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 $k \to \infty$,

$$\sigma^2_{TFP} = \sigma^2_{\eta_1^N} + \beta^2 \sigma^2_{\eta_1^I},$$

where σ^2_{TFP} denotes the variance of news shocks to TFP. With equation (16), it is easy to show that as $k \to \infty$,

$$\beta^2 \sigma^2_{\eta_1^I} = \Omega_{TFP,\eta_1^I}(k) \times \sigma^2_{TFP}. \tag{A.20}$$

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

$$\beta = \sqrt{\frac{\Omega_{TFP,\eta_1^I}(k) \times \sigma^2_{TFP}}{\Omega_{PC,\eta_1^I}(k) \times \sigma^2_{PC}}}.$$

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

8 Tables and Figures

Table 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.

Table 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.

Table 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 the 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.

Table 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 $0 \leq k \leq 120$.

Table 5: The Correlation of the News Shocks to TFP and PC Identified Under Alternative Forecast Horizons

$k \in [\underline{k}, \overline{k}]$	Corr. Coef.	$\underline{k} = \overline{k} = k$	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 $\underline{k} \leq k \leq \overline{k}$.

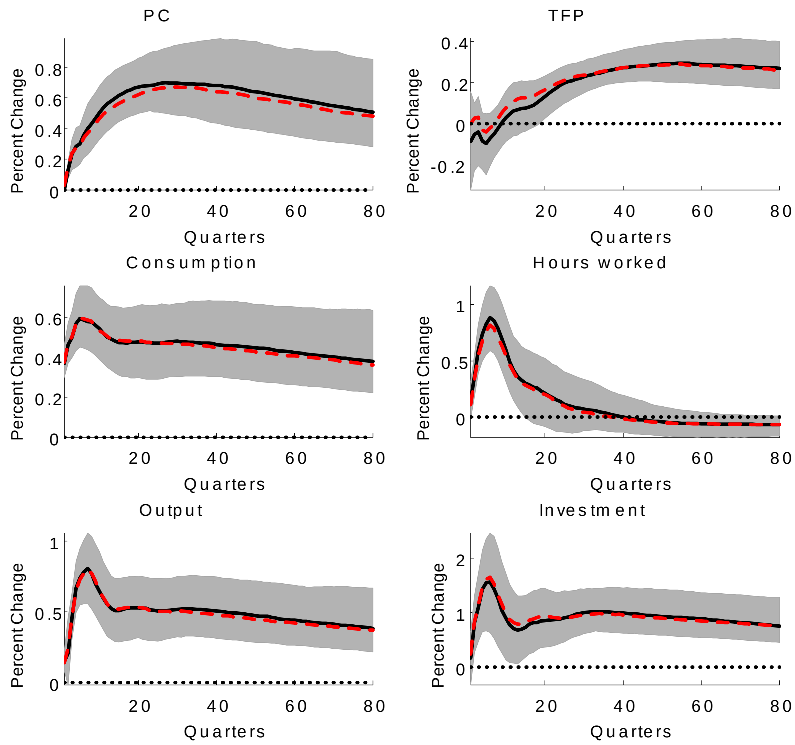

Figure 1: Impulse Responses to News Shocks to PC and TFP in the Baseline Specification

Note: 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.

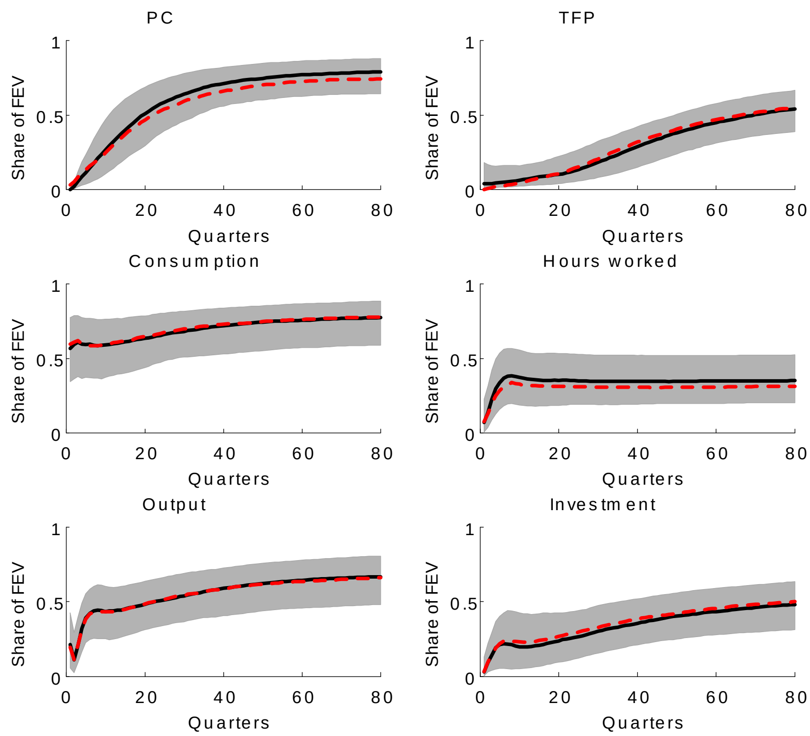

Figure 2: Share of the FEV Decomposition Attributable to News Shocks to PC and TFP in the Baseline Specification

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.

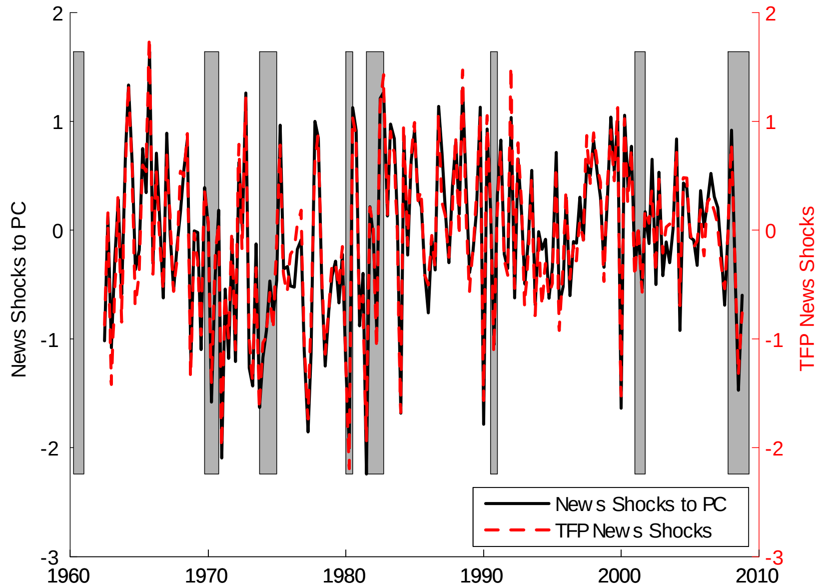

Figure 3: Time Series of the Identified News Shocks to PC and TFP and U.S. Recessions.

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.

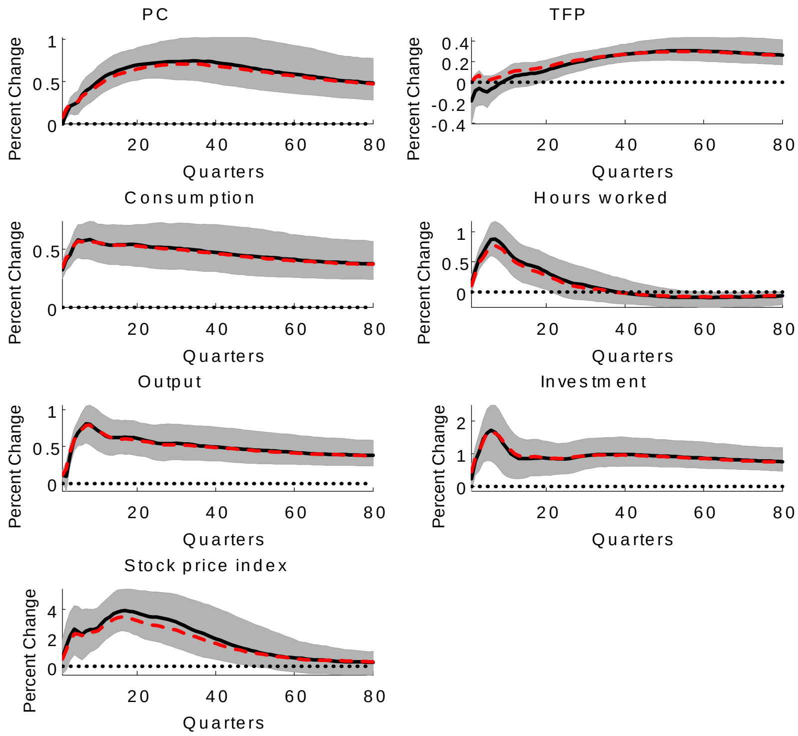

Figure 4: Impulse Responses to News Shocks to PC and TFP in the Larger System with Stock Prices

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.

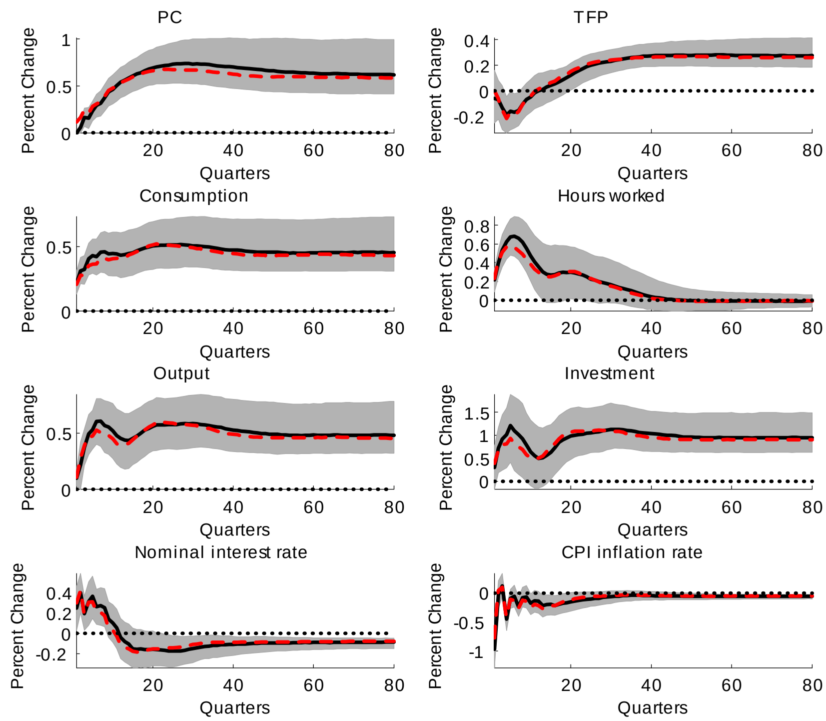

Figure 5: Impulse Responses to News Shocks to PC and TFP in the Larger System with Nominal Variables

Note: 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.

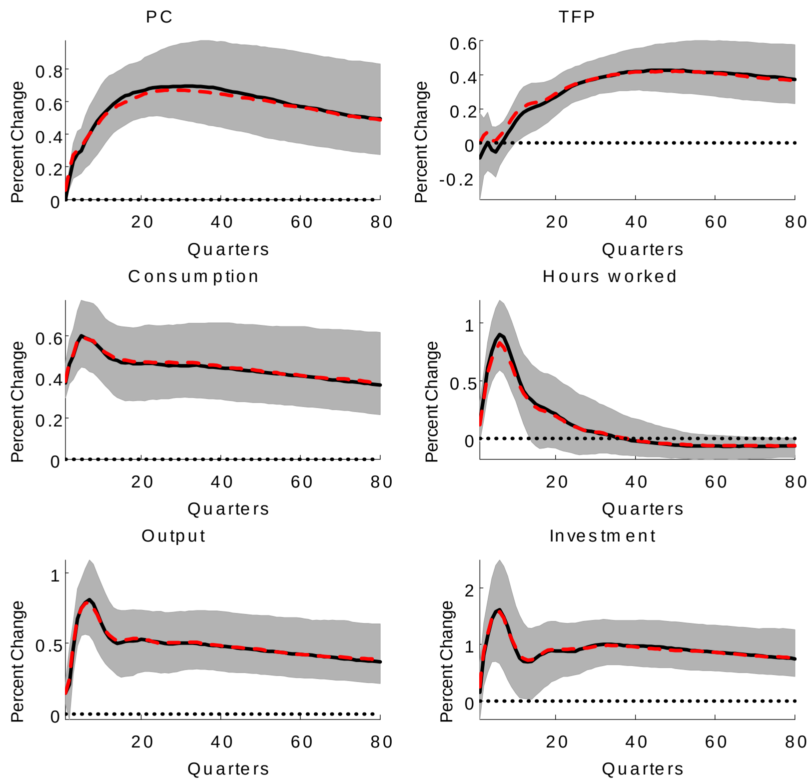

Figure 6: Impulse Responses to News Shocks to PC and TFP in the System with Consumption-sector TFP

Note: 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.

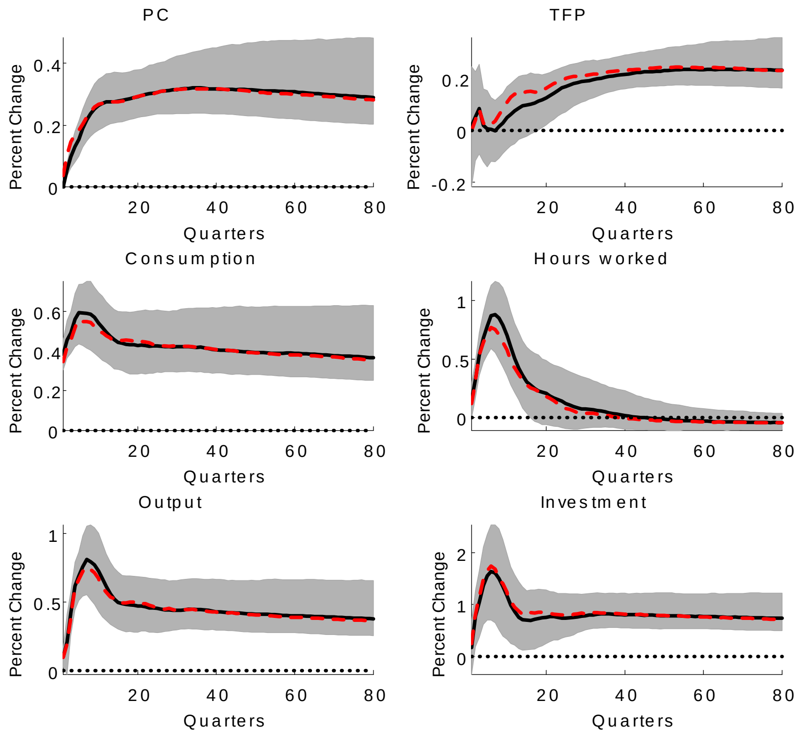

Figure 7: Impulse Responses to News Shocks to PC and TFP in the System with the GCV Investment Deflator

Note: 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.

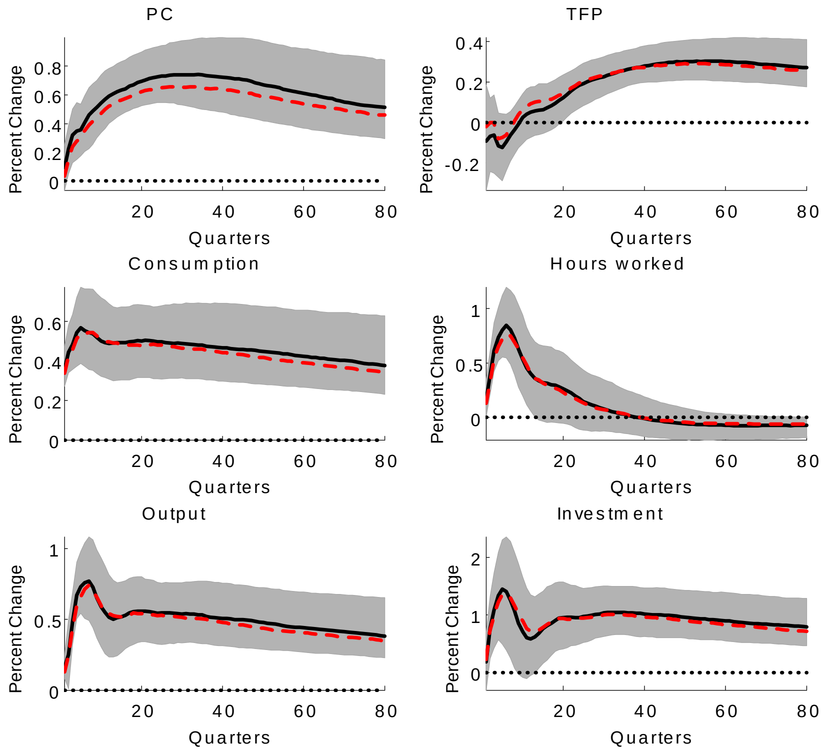

Figure 8: Impulse Responses to News Shocks to PC and TFP Identified Without Zero Restrictions

Note: 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.

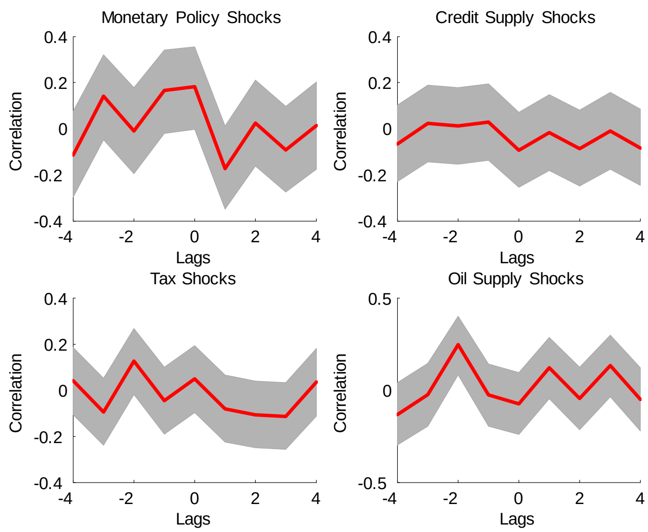

Figure 9: Cross-correlation between the News Shocks to PC and Leads/Lags of Other Macroeconomic Shocks

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

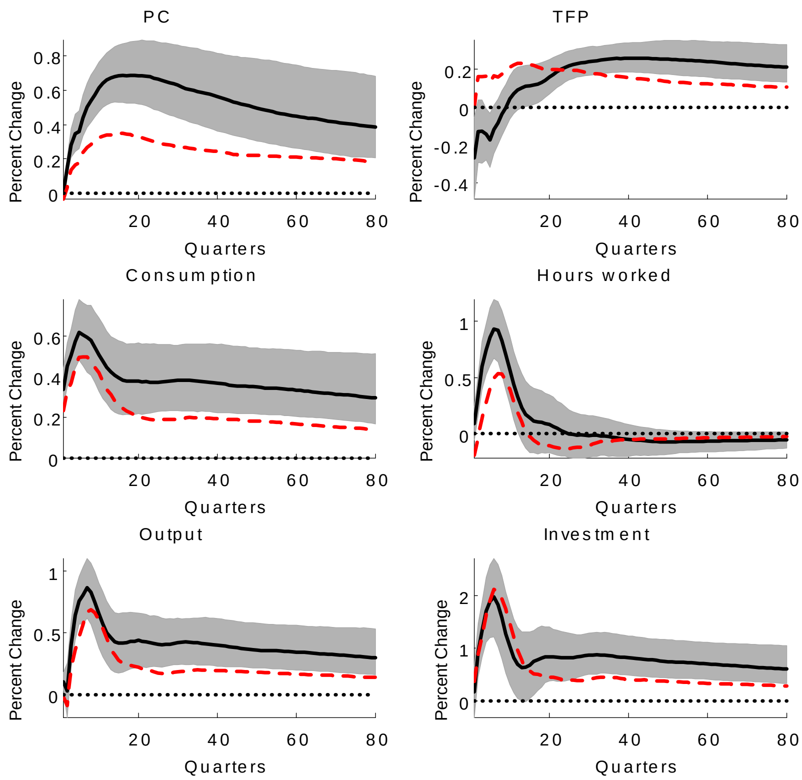

Figure 10: Impulse Responses to News Shocks to PC and TFP Identified with the Range of Forecast Horizons $\overline{k} = 40$

Note: 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.

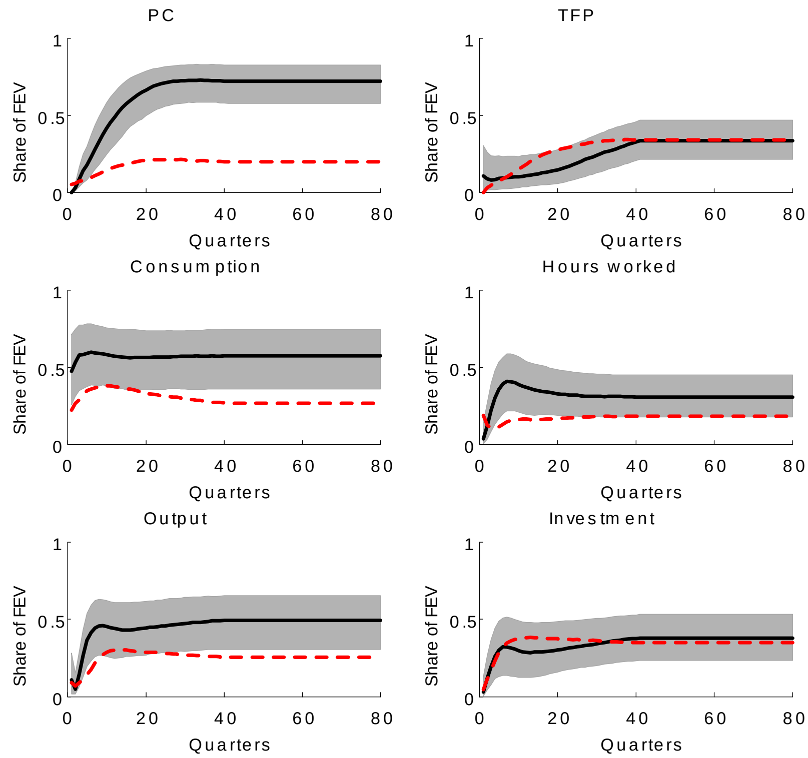

Figure 11: Share of FEV Decomposition Attributable to News Shocks to PC and TFP Identified with the Range of Forecast Horizons $k \in [0, 40]$

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 $0 \le k \le 40$. 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.

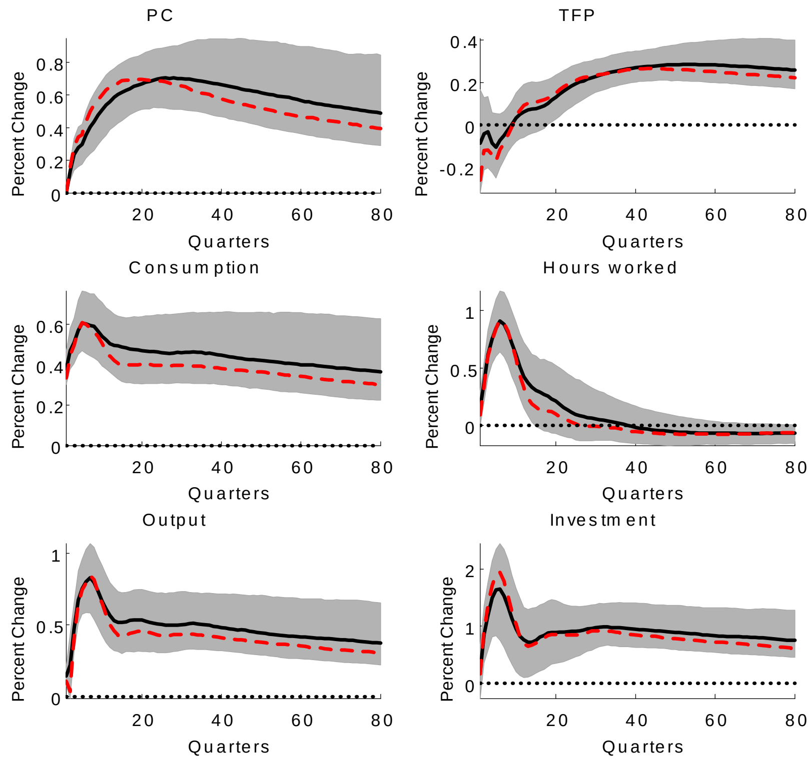

Figure 12: Impulse Responses to News Shocks to PC Identified with the Range of Forecast Horizons $k \in [0, 40]$ and $k \in [0, 120]$

Note: 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.

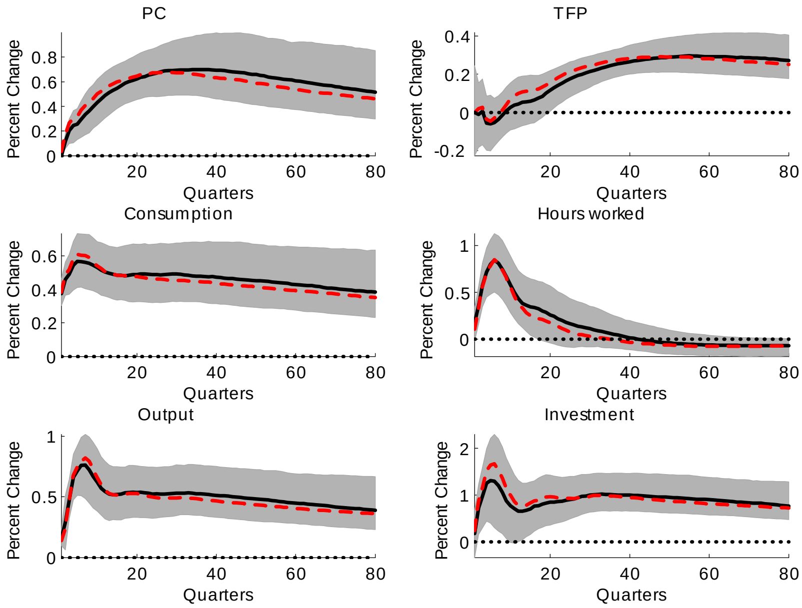

Figure 13: Impulse Responses to the News Shocks to PC and TFP Identified with the Range of Forecast Horizons $\underline{k} = \overline{k} = 40$

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.