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Investment-specific technological changes: The source of long-run TFP fluctuations

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ABSTRACT

Technological innovations originating in the capital–producing sector may spillover to the rest of the economy and enhance aggregate TFP in the long-run. This paper assesses the quantitative importance of investment-specific technological changes in long-run movements in aggregate TFP. To this end, we construct a two-sector business cycle model where an IST diffusion process influences long-run movements in aggregate TFP via spillover. We then establish the linkage between the primitive shocks of the model and two shocks that can be identified from a VAR approach: one shock accounting for the long-run movement in aggregate TFP and the other accounting for the long-run movement in the inverse of the relative price of investment. We show analytically that the correlation of these two long-run shocks can be fruitful in distinguishing the quantitative importance of IST innovations in long-run movements in aggregate TFP. Using post-war U.S. data, we find that these two long-run shocks identified by the MFEV approach are almost perfectly collinear. Moreover, these two shocks can explain a significant, and surprisingly similar, fraction of the business-cycle fluctuations in other important macro variables. Our findings suggest that embodied technological changes are an important driver of long-run movements in aggregate TFP.

1. Introduction

There has been an ongoing debate in the macro literature about the importance of technological innovations for business cycles. Following the seminal work of Kydland and Prescott (1982), earlier papers model technological innovations as either temporary or permanent disturbances to neutral technology, measured as Total Factor Productivity (TFP henceforth). Recent studies, however, contend that technological innovations may not come through increases in TFP but rather through the introduction of new, more efficient capital goods triggered by a fall in the relative price of investment – the so-called "investment-specific technological changes".[1] Nonetheless, a common theme underlying both arguments is that neutral and investment-specific technological innovations are assumed to follow orthogonal stochastic processes, such that changes in TFP are independent of changes in the relative price of investment.[2] In reality, however, a technological innovation

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[1] See, for example, the seminal work by Greenwood et al. (1997) and Fisher (2006).

[2] For example, Fisher (2006) assumes that both the neutral and the investment-specific technology shocks follow independent nonstationary process and derives long-run restrictions to identify IST and neutral technology shocks in a VAR. Similarly, Altig et al. (2011) apply the same restrictions to identify long-run shocks. Under such assumptions, the TFP and the relative price of investment series would not share any joint long-run properties.

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originating in one sector of the economy, such as the capital-producing sector, may spillover to the rest of the economy over the span of many years and enhance aggregate TFP in the long-run. Such spillover effects suggest that, as general purpose technologies, investment-specific technological innovations may be important sources of long-run movements in aggregate TFP and short-run fluctuations.

This paper therefore assesses the quantitative importance of investment-specific technological (" IST" henceforth) changes in long-run movements in aggregate TFP. To this end, we construct a two-sector business cycle model that features technology diffusion and spillover. A novel feature of our model is that permanent IST shocks affect TFP of not only the capital-producing sector, but also the consumption sector via spillover.[3] Accordingly, in our model, both aggregate TFP and the relative price of investment share the IST diffusion process as a common component. For generality, our model incorporates various other permanent and transitory shocks to TFP and to the relative price of investment, and allows for technology spillover from both sectors. To quantify the importance of IST spillover, we construct two long-run shocks that we later identify from a VAR approach: one shock accounting for the long-run movement in aggregate TFP and the other accounting for the long-run movement in the inverse of the relative price of investment. By establishing the linkage between the primitive shocks of the model and these two long-run shocks, we show analytically that, in this general setup, both the *magnitude* and the *sign* of the correlation of these two long-run shocks can be fruitful in distinguishing the quantitative importance of IST innovations in long-run movements in aggregate TFP.

Empirically, we identify two long-run shocks sequentially with the maximum forecast error variance approach ("MFEV" henceforth): a shock to the inverse of the relative price of investment and a shock to aggregate TFP. Using post-war U.S. data, we find that these two identified shocks are almost perfectly collinear if each is identified by maximizing the FEV of the corresponding variable at a finite, but sufficiently long, horizon. In particular, the impact response ("IRF" henceforth) of TFP to the shock to the inverse of the relative price of investment ("PC" henceforth) is essentially zero. In the long run, by contrast, the shock to PC can explain more than 50 percent of TFP fluctuations. Similarly, while PC responds little on impact to the shock to aggregate TFP, more than 70 percent of its long-run variations can be explained by this shock. Moreover, both shocks incur almost identical IRFs on various macro variables and can explain a significant fraction of the fluctuations of consumption, hours worked, and output over business cycles. The similarity of the IRFs is further confirmed by a correlation coefficient of 0.9690 between the two identified shocks. This high correlation between the two identified shocks is very robust to adding more variables, different lags, alternative TFP series, alternative measures of investment deflators, alternative empirical specification, and a split sample. The quasi-identity of our identified shocks suggests that embodied technological changes is one main source of long-run movements in aggregate TFP.

Our paper contributes to the business cycle literature from several perspectives. First, most studies in this literature, either theoretically or empirically, treat aggregate TFP shocks and IST shocks as separate drivers of business cycles. Such an assumption is inconsistent with the recent empirical findings of Schmitt-Grohé and Uribe (2011), who show that TFP and the relative price of investment have a common stochastic trend. A similar finding is made by Benati (2015), although the latter argues that TFP and the relative price of investment may not necessarily be cointegrated. Our paper takes a step further. The spillover result we find provides an interpretation of the common shock underlying the long-run fluctuations in PC and TFP, as have been found by both papers. More importantly, it shifts the question from the debate over whether PC and TFP are cointegrated to the understanding of the source of this common component and its quantitative importance to the long-run variations in TFP. Moreover, by establishing the linkage between the primitive shocks of our model and the two long-shocks identified from a VAR approach, our paper provides a direct measure of the magnitude and the direction of spillover. On the empirical ground, different from most of the literature that uses long-run restrictions as an identification scheme, this paper adopts the MFEV approach to identify sequentially the two long-run shocks, consistent with the idea that the permanent IST shock is a common driver of the long-run movements in both TFP and the relative price of investment. We view our work as a useful complement to Schmitt-Grohé and Uribe (2011) from both theoretical and empirical perspectives.

Our findings also provide new insight into the role of IST shocks in business cycles. Both Fisher (2006) and Justiniano et al. (2011) argue that investment-specific shocks are the main sources of business cycles.[4] Our results provide additional support for the quantitative importance of permanent IST shocks for business cycles. More importantly, our empirical findings suggest that the mechanism for IST shocks to impact the business cycle may well be different from the conventional mechanism.[5] The crucial role of permanent IST innovations in long-run movements in aggregate TFP suggests that one potentially important channel for the IST shock to drive business cycles may be through influencing consumer confidence that is based on long-run movements in aggregate TFP. Such a channel, we argue, may lead to a negative comovement between stock price and the relative price of investment, a puzzle from the perspective of standard business cycle models.

In addition, our empirical findings provide additional support for the role of investment-specific technological changes as general purpose technology. It has long been argued that investment-specific technological changes are important sources

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

[4] Recently, Jaimovich and Rebelo (2009) and Schmitt-Grohé and Uribe (2012) argue for the importance of IST news shocks in business cycles.

[5] In conventional business-cycle models (e.g., Greenwood et al. 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.

of productivity growth in the U.S. Using industry-level data, Commins and Violante (2002) and Basu et al. (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 technological changes represent a general purpose technology. Moreover, Jorgenson et al. (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. Meanwhile, several papers study the implications of technological diffusion for business cycles, beyond its role for long-run productivity growth.[6] Our paper is the first to identify the quantitative importance of IST innovations to long-run movements in aggregate TFP from a VAR-based approach, thus providing a useful complement to this literature.

The remaining sections are structured as follows. In Section 2, we provide a model with technology spillover and establish the linkage between the primitive shocks in this model and the two long-run shocks that can be identified by a VAR approach. In Section 3, we present our empirical strategy to identify the two long-run shocks. In Section 4, we present the data and discuss the specifications of the VAR. In Section 5, we provide our empirical results estimated using post-war U.S. data. Section 6 concludes.

2. A model of technology diffusion and spillover

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. Our focus is then to establish a linkage between the primitive shocks of the model and the two long-run shocks that we later identify from a VAR approach. Based on this mapping, we show that the correlation of the two long-run shocks can be fruitful in measuring the quantitative importance of IST changes in long-run TFP fluctuations.

2.1. Environment

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-good producing sector equals the inverse of the relative price of investment goods, making the two-sector model isomorphic to the one-sector business cycle model with IST. Later, we explore the relationship between the relative TFP and the relative price of investment when the above assumptions are violated.

In this framework, the measured sectoral TFP is equivalent to the sectoral technology. Therefore, we define $\Phi_t \equiv TFP^I_t/TFP^C_t$ 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:

$$Y_t = C_t + I_t \cdot P^I_t/P^C_t,$$

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

$$\log TFP^I_t/TFP^C_t = \log P^C_t/P^I_t \equiv \log PC_t, \tag{1}$$

where for notational simplicity, we denote $P^C_t/P^I_t \equiv PC_t$.

In practice, however, there is no reason to expect that Eq. (1) 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 inverse of the relative price of investment and the relative TFP of the investment-good producing sector.[7] Finally, factors driving a wedge between firm-level TFP and technology include

[6] See, for example, Lippi and Reichlin (1994), Jovanovic and Lach (1997), Andolfatto and MacDonald (1998), Rotemberg (2003) and Comin et al. (2009).

[7] See also Justiniano et al. (2011), Basu et al. (2013, "BFFK" henceforth), and Ben Zeev and Khan (2013) for a discussion.

returns to scale, markup, capital utilization, and allocative efficiency, which implies a further wedge between the relative technology and the relative price.[8]

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

$$\log PC_t = \log \Phi_t + \varpi_t + \omega_t. \tag{2}$$

In Eq. (2), ϖ_t (ω_t) is a permanent (stationary) component of the inverse of the relative price of investment and both components are orthogonal to Φ_t. Specifically, $\varpi_t = \varpi_{t-1} + \upsilon_{1t}$, 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 $\upsilon_{2t} \sim N\left(0, \sigma^2_{\upsilon_2}\right)$. Equation (2) implies that even long-run fluctuations in PC can be affected by shocks other than IST changes. However, as Basu et al. (2013, Fig. 2) found, PC and the relative TFP of the investment-good producing sector track each other fairly well over long periods of time, though these two series can diverge in the short 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.[9] In Appendix 7.2, we show that the log difference of aggregate TFP can be proxied by a weighted sum of the log difference of sector-specific TFP.[10]

$$\Delta \log TFP_t = (1 - w^I)\Delta \log TFP^C_t + w^I \Delta \log TFP^I_t, \tag{3}$$

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.[11] Given the definition of Φ, changes in aggregate TFP can be rewritten as

$$\Delta \log TFP_t = \Delta \log TFP^C_t + w^I \Delta \log \Phi_t. \tag{4}$$

Without loss of generality, we can further normalize the levels of $\log TFP_t$, $\log TFP^C_t$, and $\log \Phi_t$ at period 0 to be zero.[12] Since Eq. (4) holds for all period t, it implies that

$$\log TFP_t = \log TFP^C_t + w^I \log \Phi_t. \tag{5}$$

According to Eq. (5), 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 (5). 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.[13]

Second, improvement in Φ may lead to improvement in the productivity of consumption-goods producing sector, 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.[14] The focus of this paper is to quantify the contribution of IST improvements to long-run aggregate TFP fluctuations via the spillover effect.

2.2. Technology diffusion and spillover

The above general model setup 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^C_t, or equivalently, the specifications of TFP^I_t and TFP^C_t. In this section, we first present a baseline framework to capture the idea that improvements in IST spill over to the consumption-sector TFP over time. We then generalize the framework to allow for technology spillover in both directions. In each case, we establish the linkage between the primitive shocks of our model and the long-run shocks to TFP and PC that we later identify from a VAR approach, and derive analytically the relationship between the correlation of the two long-run shocks and the contribution of IST innovations to long-run movements in aggregate TFP.

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

[9] 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.

[10] 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.

[11] Strictly speaking, w^I is time-varying. However, as found by Fernald (2012), the equipment and consumer durables as a share of business output is fairly stable around 0.20 in the U.S. data. Hence, for tractability, we assume a constant investment share throughout the paper.

[12] 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.

[13] See Greenwood et al. (1997) for a discussion.

[14] For example, Commins 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 et al. (2004) find that industries with high ICT capital growth rates in the 1987–2000 period had faster acceleration in TFP growth in 2000.

2.2.1. Spillover from IST to consumption-sector TFP

Consider a specification where innovations to IST involve a diffusion process that increases productivity only gradually. For comparison, the neutral technology includes a similar diffusion process. In addition, we allow for the presence of temporary disturbances to both types of technology. This delivers the following data-generating process for IST and TFP of the consumption sector:

$$\log \Phi_t = \sum_{i=0}^{\infty} d_i^I \eta_{1,t-i}^I + \nu_t^I, \tag{6}$$

$$\log TFP_t^C = \sum_{i=0}^{\infty} d_i^N \eta_{1,t-i}^N + \nu_t^N + \alpha \sum_{i=0}^{\infty} \left(d_i^I - d_i^K\right) \eta_{1,t-i}^I, \tag{7}$$

where

$$d_i^J = 1 - c_J(\delta_J)^i, \quad 0 \le \delta_J < 1, \quad c_J > 0, \quad J = I \text{ or } N, \tag{8}$$

$$d_i^K = c_K(\delta_K)^i\left[1 - (\delta_K)^i\right], \quad c_K > 0, 0 \le \delta_K < 1, \tag{9}$$

$$\nu_t^J = \rho^J \nu_{t-1}^J + \eta_{2,t}^J, \quad 0 \le \rho^J < 1, \quad J = I \text{ or } N. \tag{10}$$

$\eta_1^I \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{\eta_1^I}\right)$, $\eta_1^N \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{\eta_1^N}\right)$, $\eta_2^I \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{\eta_2^I}\right)$, and $\eta_2^N \overset{i.i.d.}{\sim} N\left(0, \sigma^2_{\eta_2^N}\right)$. By construction, all primitive shocks are orthogonal to each other.[15] In addition, all permanent or transitory technology shock are orthogonal to both the permanent and transitory shocks to the wedge between PC and IST.

The component $\sum_{i=0}^{\infty} d_i^J \eta_{1,t-i}^J$ ($J = I$ or N) is a diffusion process for either investment-specific technology or neutral technology, denoted with superscript I and N, respectively. δ_J measures the diffusion speed: a higher δ_J implies a slower diffusion. In general, the diffusion speed for the two types of technology can be different, i.e., $\delta_I \ne \delta_N$. c^J ($J = I$ or N) captures the cost of implementing or learning by individual firms in each sector for a technology innovation in the same sector.[16] Moreover, the effect of η_1^I on Φ is assumed to grow over time $\left(d_i^I \le d_{i+1}^I\right)$ and the long-run effect is normalized to 1. Thus, the innovation η_1^I contains permanent innovations to the investment-specific technology. We therefore call η_1^I the permanent IST 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.

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. Specifically, given the diffusion process, the value of α captures the elasticity of TFP^C with respect to the permanent IST shock η_1^I in the long run.[17] In standard business cycle models (e.g. Greenwood et al., 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 the productive efficiency gain brought by 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 et al. (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.[18] Finally, d_i^K is the efficiency loss during the spillover of IST innovations to the consumption sector. Such an efficiency loss may be due to the aggregate fixed cost associated with the complementary investments in the consumption-sector to derive the full benefit of IST innovations. Note that d_i^K is hump-shaped along the time dimension i, which captures the fact that as the fraction of consumption-sector firms introducing the ICT technology increases, each firm is subject to a smaller fixed cost due to a positive externality from technology adoption by other firms.[19]

[15] 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.

[16] Note that, by definition, a neutral technology innovation occurs in both sectors of the economy simultaneously.

[17] 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.

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

[19] Cohen and Levinthal (1989) demonstrate that knowledge spillovers can induce complementarities in R&D efforts to increase the absorptive capacity of knowledge. They also argue that a product innovation developed on the basis of a well-established underlying knowledge base will diffuse more rapidly among users than one grounded in a more recently developed body of scientific knowledge, consistent with our assumption that as more firms adopt the technology, the fixed adjustment cost declines. See also Aghion and Jaravel (2015) for an application of this idea for the growth literature.

We now express TFP in terms of primitive shocks. Plugging Eqs. (6) and (7) into (5), we can rewrite aggregate TFP as

$$\log TFP_t = \sum_{i=0}^{\infty} d_i^N \eta_{1,t-i}^N + \sum_{i=0}^{\infty} \left(\beta d_i^I - \alpha d_i^K\right) \eta_{1,t-i}^I + \nu_t, \tag{11}$$

where $\beta \equiv \alpha + w^I$ captures the overall contribution of the permanent IST shock to aggregate TFP, and $\nu_t \equiv w^I \nu_t^I + \nu_t^N$ captures the transitory component of aggregate TFP. Equation (11) implies that the impact of the permanent IST shock on aggregate TFP can be negative in the initial periods, before it becomes positive in the long run. This is because, in the short run, the efficiency loss associated with the complementary investments in the consumption sector may exceed the direct benefit of introducing IST.

Equation (11) nests the diffusion process of TFP adopted in Beaudry and Portier (2006), who assume that there is a single diffusion process on TFP plus a single transitory shock.[20]

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

where $d_i = 1 - \delta^i$, $0 \le \delta < 1$. Absent the direct and the spillover effects of the permanent IST shock on measured TFP, the shock to aggregate TFP is equivalent to the shock to neutral technology. This view, however, may not hold in light of the potential spillover effect of the permanent IST shock on aggregate TFP fluctuations. Also, our diffusion process differs from that of Beaudry and Portier (2006) in that we do not impose the zero impact restriction, since our identification scheme is independent of whether there is a zero impact restriction or not. Finally, in our model, the effect of technology diffusion on aggregate TFP can be non-monotonic with respect to time, due to the presence of efficiency loss incurred when firms in the consumption sector introduce IST.

We now explore the contribution of the permanent IST shock to aggregate TFP and PC at a specific horizon. According to Eq. (11), the contribution of the permanent IST shock η_1^I to the fluctuations of aggregate TFP hinges on the magnitude of β, which further depends on the spillover effect α. The larger is the spillover effect, the larger is the contribution of η_1^I to aggregate TFP fluctuations. By contrast, under the standard business cycle 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 permanent IST shock to aggregate TFP can be measured by the share of the forecast error variance (FEV) of aggregate TFP attributable to the permanent IST shock η_1^I, k quarters ahead, denoted as $\Omega_{TFP,\eta_{1,t}^I}(k)$.

$$\Omega_{TFP,\eta_1^I}(k) = \frac{\sigma_{\eta_1^I}^2 \sum_{j=0}^{k-1} \left(\beta d_j^I - \alpha d_j^K\right)^2}{\Omega_{TFP}(k)}, \tag{12}$$

where $\Omega_{TFP}(k)$ denotes the forecast error variance of aggregate 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 permanent IST 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. Intuitively, the contribution of the permanent IST shock to aggregate 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 $k \to \infty$, Eq. (12) becomes

$$\Omega_{TFP,\eta_1^I}(k) = \frac{1}{1 + \sigma_{\eta_1^N}^2 / \left(\beta^2 \sigma_{\eta_1^I}^2\right)}. \tag{13}$$

Equation (13) shows that, in the long run, the share of the FEV of aggregate TFP attributable to the permanent IST shock depends positively on $\beta^2 \sigma_{\eta_1^I}^2 / \sigma_{\eta_1^N}^2$, which is the contribution of the permanent IST 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 aggregate TFP becomes essentially zero.

Similarly, we can derive the FEV of PC attributable to the permanent IST shock k quarters ahead. Combining Eq. (2) with (6), 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 permanent IST shock k quarters ahead, which we denote as $\Omega_{PC,\eta_1^I}(k)$, is

$$\Omega_{PC,\eta_1^I}(k) = \frac{\sigma_{\eta_1^I}^2 \sum_{j=0}^{k-1} \left(d_j^I\right)^2}{\Omega_{PC}(k)}, \tag{14}$$

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

where $\Omega_{PC}(k)$ denotes the FEV of PC k-step ahead. Appendix 7.3 shows that as $k \to \infty$, Eq. (14) becomes

$$\Omega_{PC,\eta_1^I}(k) = \frac{1}{1+\sigma_{\upsilon_1}^2/\sigma_{\eta_1^I}^2}. \tag{15}$$

Eqs. (13) and (15) imply that the same primitive shock—the permanent IST shock—would maximize the FEVs of both TFP and PC in the long run only if the spillover effects of the permanent IST shock is sufficiently large and the permanent IST shock plays a dominant role in the long-run fluctuations in PC.

Two approaches may potentially quantify the magnitude of the effects of the permanent IST shock on long-run fluctuations in aggregate TFP. One is to identify the permanent IST shocks directly by estimating the structural model, and compute the contribution of such shocks to long-run fluctuations in aggregate TFP. This approach, although conceptually appealing, is confronted with the difficulty of finding a suitable identification scheme of permanent IST shocks in the presence of other permanent or temporary shocks to PC. The other approach, as we adopt in this paper, is to identify by VAR the two shocks that account for the long-run movements in TFP and PC, respectively, and use the correlation of these two empirically identified long-run shocks as a measure of the quantitative importance of permanent IST shocks to long-run TFP fluctuations. Intuitively, the higher is the contribution of permanent IST shocks to the long-run fluctuation of TFP via spillover, the higher is the correlation of the two long-run shocks identified from a VAR approach.

In the remaining part of this section, we first establish the linkage between the primitive shocks η in our model and the long-run shocks to PC and TFP. We then analytically derive the correlation of the two long-run shocks and show both the magnitude and the sign of such a correlation shed light on the importance of the permanent IST shock in long-run movements in aggregate TFP. We leave the choice of empirical strategies to identify the two long-run shocks into the next section.

According to our model, a combination of the permanent IST shock and the permanent wedge between IST and PC explain fully the long-run fluctuations in PC. Hence, we construct a shock that accounts for the long-run fluctuations in PC, ε_t^{PC}, as

$$\varepsilon_t^{PC} = \eta_{1t}^I + \upsilon_{1t}. \tag{16}$$

Similarly, a combination of the permanent innovations to IST and neutral technology can explain fully the long-run fluctuations in TFP. Hence, we also construct a shock that accounts for the long-run fluctuations in TFP, ε_t^{TFP}, as

$$\varepsilon_t^{TFP} = \beta\eta_{1t}^I + \eta_{1t}^N. \tag{17}$$

Equation (16) suggests that the long-run shock to the inverse of the relative price of investment (PC) may not be identical to the permanent IST shock. Nonetheless, the importance of the permanent IST shock for long-run fluctuations in PC can still be verified by examining the share of the FEV of PC attributable to the permanent TFP shock. Given that the permanent IST 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 permanent TFP shock in the long run, as later shown by our empirical evidence, implies that the permanent IST shock plays a dominant role in the long-run fluctuations in PC.

The correlation coefficient between the long-run shocks to PC and TFP can, therefore, be expressed as follows:

$$\rho\left(\varepsilon_t^{PC}, \varepsilon_t^{TFP}\right) = \frac{1}{\sqrt{1+\sigma_{\eta_1^N}^2/\left(\beta^2\sigma_{\eta_1^I}^2\right)}\sqrt{1+\sigma_{\upsilon_1}^2/\sigma_{\eta_1^I}^2}}. \tag{18}$$

The right-side of Eq. (18) is (the square root of) the product of the share of the FEVs of TFP and PC attributable to the permanent IST shock as $k \to \infty$. Intuitively, the correlation of these two long-run shocks depends on how important the permanent IST shock is to long-run movements in both aggregate TFP and PC, captured by $\beta^2\sigma_{\eta_1^I}^2$ and $\sigma_{\eta_1^I}^2$ respectively, relative to other permanent shocks. Hence, a high correlation is achieved *only if* the spillover effect of the permanent IST shock is sufficiently large and the permanent IST shock plays a dominant role in the long-run fluctuations in PC.

Note that a high correlation between the two long-run shocks only requires that the process of PC and TFP share a common stochastic trend, which plays a dominant role in determining the long-run movement in PC and TFP. Such a common stochastic trend, however, may not necessarily be the only stochastic trend underlying the process of TFP or PC, as required by cointegration. Hence, as a measure of the spillover effect of permanent IST shocks, the correlation of the two long-run shocks allows us to understand the source of this common stochastic component and its quantitative importance to the long-run variations in TFP, without testing whether these two series are cointegrated.

Finally, we must ask how much of the overall contribution of the permanent IST 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 7.4 shows that as $k \to \infty$, β equals

$$\beta = \sqrt{\frac{\Omega_{TFP,\eta_1^I}(k) \times \sigma_{TFP}^2}{\Omega_{PC,\eta_1^I}(k) \times \sigma_{PC}^2}}, \tag{19}$$

where σ_{TFP}^2 and σ_{PC}^2 denote the variances of shocks to aggregate 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.

2.2.2. Spillover in both directions

In our baseline framework, we assume that the permanent IST shock is the only common long-run shock to PC and consumption-sector TFP. In practice, however, technology innovations may occur in the consumption-good producing sector, which we call "consumption-specific technology", and spillover to the investment-good producing sector. This renders shocks to consumption-specific technology an alternative candidate of the common driving force underlying TFP and PC. Therefore, in this section, we discuss the validity of our identification scheme in a more general setting that allows for spillover in both directions.[21] We show that the correlation between the shocks on TFP and PC would be negative if the spillover from the consumption to the investment-good producing 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 long-run shocks sheds light on whether the permanent IST shock or the shock to consumption-specific technology dominate the underlying common driving force of TFP and PC.

To nest spillover in both directions, we adopt an alternative specification in which sector-specific TFP are expressed in terms of some exogenous processes. Specifically, we assume

$$\begin{bmatrix} \log TFP_t^C \\ \log TFP_t^I \end{bmatrix} = B \begin{bmatrix} \epsilon_t^C \\ \epsilon_t^I \\ \epsilon_t^{C,I} \\ \epsilon_t^{I,C} \end{bmatrix}, \tag{20}$$

where

$$B = \begin{bmatrix} B_{11} & B_{12} & B_{13} & B_{14} \\ B_{21} & B_{22} & B_{23} & B_{24} \end{bmatrix}$$

is a matrix of structural parameters. ϵ_t^j, for sector $j \in \{C, I\}$, captures the productive efficiency gain that results from technology innovations in sector j, whereas $\epsilon_t^{i,j}$ for i and $j \in \{C, I\}$ captures the efficiency loss during the technology spillover from sector j to i, which may, again, be explained by the fixed cost associated with the complementary investment by firms in sector i to adopt technology innovated in sector j. Later, we show that both ϵ_t^j and $\epsilon_t^{i,j}$ contain permanent technology shocks to sector j. Equation (20) implies that TFP at each sector can be expressed as

$$\begin{aligned} \log TFP_t^C &= B_{11}\epsilon_t^C + B_{12}\epsilon_t^I + B_{13}\epsilon_t^{C,I} + B_{14}\epsilon_t^{I,C} \\ \log TFP_t^I &= B_{21}\epsilon_t^C + B_{22}\epsilon_t^I + B_{23}\epsilon_t^{C,I} + B_{24}\epsilon_t^{I,C} \end{aligned} \tag{21}$$

If there exists investment-specific technology, by definition, $B_{22} = 1 + B_{12}$, where the direct impact of IST on TFP^I is normalized to 1. $B_{12} \geq 0$ captures the magnitude of the spillover effect of IST on consumption-sector TFP. Also, $B_{23} = B_{13} = -B_{12} \leq 0$, capturing the magnitude of efficiency loss due to fixed cost that firms in consumption sector pay to fully utilize the IST technology. 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. Accordingly, without IST spillover, $B_{23} = B_{13} = 0$. Similarly, if there exists consumption-specific technology, by definition, we have $B_{11} = 1 + B_{21}$, with the spillover effect captured by $B_{21} \geq 0$. Moreover, $B_{14} = B_{24} = -B_{21} \leq 0$. By contrast, if there is no consumption-specific technology, $B_{11} = B_{21}$ and $B_{14} = B_{24} = 0$.

To interpret shocks to the inverse of the relative price of investment, we would like to define the relative TFP of the investment-good producing sector, $\log \Phi_t \equiv \log TFP_t^I - \log TFP_t^C$, and map it into the primitive shocks according to Eqs. (20) and (21). Since, by construction, $B_{23} = B_{13}$ and $B_{14} = B_{24}$, we have

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

According to Eq. (22), Φ_t hinges on both ϵ_t^I and ϵ_t^C due to the potential spillover in either direction. Specifically, a positive ϵ_t^I tends to increase the relative TFP of the investment-good producing sector, while a positive ϵ_t^C does the opposite.

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

$$\log TFP_t = F^C \epsilon_t^C + F^I \epsilon_t^I + F^{C,I} \epsilon_t^{C,I} + F^{I,C} \epsilon_t^{I,C}, \tag{23}$$

where

$$\begin{aligned} &F^I \equiv w^I B_{22} + (1 - w^I) B_{12}, \quad F^C \equiv w^I B_{21} + (1 - w^I) B_{11}, \\ &F^{C,I} \equiv w^I B_{23} + (1 - w^I) B_{13}, \quad F^{I,C} \equiv w^I B_{24} + (1 - w^I) B_{14}. \end{aligned}$$

Note that, the larger is the spillover from IST to the consumption-sector TFP (B_{12}), the larger is F^I, the contribution of ϵ_t^I to aggregate TFP. Similarly, the larger is the spillover from the consumption-specific technology to investment-sector TFP (B_{21}), the larger is F^C, which is the contribution of ϵ_t^C to aggregate TFP.

The above model nests both standard business cycle models with IST and the model of IST spillover that we described in the previous section. The standard business cycle model with IST shocks only assumes no spillover. This corresponds to the

[21] We thank one referee for this suggestion.

case that $B_{11}=B_{21}=1$, $B_{22}=1, B_{12}=0$, $B_{23}=B_{13}=B_{24}=B_{14}=0$. Accordingly, Eqs. (22) and (23) can be rewritten as

$$\log \Phi_t = \epsilon_t^I,$$
$$\log TFP_t = \epsilon_t^C + w^I \epsilon_t^I.$$

Again, ϵ_t^I affects aggregate TFP only through the direct effect via w^I. By contrast, if we allow for IST spillover but without spillover from consumption sector, as our baseline framework shows, $B_{22}=1+B_{12}$, where $B_{12}>0$. Moreover, $B_{23}=B_{13}=-B_{12}<0$ and $B_{24}=B_{14}=0$ and $B_{11}=B_{21}=1$. Accordingly, Eqs. (22) and (23) can be rewritten as

$$\log \Phi_t = \epsilon_t^I,$$
$$\log TFP_t = \epsilon_t^C + w^I \epsilon_t^I + B_{12}\left(\epsilon_t^I - \epsilon_t^{C,I}\right).$$

It is immediate that the effect of IST spillover on aggregate TFP hinges on both the magnitude of the spillover, captured by B_{12}, and the net efficiency gain of adopting IST by firms in consumption sector, measured by $\epsilon_t^I - \epsilon_t^{C,I}$.

Without loss of generality, we assume that ϵ_t^j, $j \in \{C, I\}$, contains both a diffusion process and a stationary process. By contrast, the efficiency loss associated with the technology spillover from sector j to i is only driven by permanent technology shocks:

$$\epsilon_t^I \equiv \sum_{i=0}^{\infty} d_i^I \eta_{1,t-i}^I + \nu_t^I, \quad \epsilon_t^C \equiv \sum_{i=0}^{\infty} d_i^N \eta_{1,t-i}^N + \nu_t^N,$$
$$\epsilon_t^{C,I} \equiv \sum_{i=0}^{\infty} d_i^K \eta_{1,t-i}^I, \quad \epsilon_t^{I,C} \equiv \sum_{i=0}^{\infty} d_i^L \eta_{1,t-i}^N,$$

where

$$d_i^J = 1 - c_J(\delta_J)^i, 0 \le \delta_J < 1, \quad c_J > 0, \quad J = I \text{ or } N,$$
$$d_i^H = c_H(\delta_H)^i\left[1-(\delta_H)^i\right], \quad c_H > 0, 0 \le \delta_H < 1, \quad H = K \text{ or } L,$$
$$\nu_t^J = \rho^J \nu_{t-1}^J + \eta_{2,t}^J, 0 \le \rho^J < 1, \quad J = I \text{ or } N.$$

Again, $\eta_1^I \overset{i.i.d.}{\sim} N\left(0, \sigma_{\eta_1^I}^2\right)$ and $\eta_1^N \overset{i.i.d.}{\sim} N\left(0, \sigma_{\eta_1^N}^2\right)$, $\eta_2^I \overset{i.i.d.}{\sim} N\left(0, \sigma_{\eta_2^I}^2\right)$, and $\eta_2^N \overset{i.i.d.}{\sim} N\left(0, \sigma_{\eta_2^N}^2\right)$. By construction, all primitive shocks are orthogonal to each other. In addition, all permanent or transitory technology shocks are orthogonal to both the permanent and transitory shocks to the wedge between PC and IST.

We now analytically derive the correlation of the long-run shocks to TFP and PC and establish the link between such a correlation and the importance of permanent IST shocks in long-run aggregate TFP fluctuations. In this general framework, a shock that accounts for the long-run fluctuations in PC simply maps into a linear combination of the two permanent technology shocks and the permanent wedge between PC and IST:

$$\varepsilon_t^{PC} = (B_{22}-B_{12})\eta_{1t}^I - (B_{11}-B_{21})\eta_{1t}^N + \upsilon_{1t}. \tag{24}$$

Similarly, a shock that accounts for the long-run fluctuations in aggregate TFP maps into

$$\varepsilon_t^{TFP} = F^I \eta_{1t}^I + F^C \eta_{1t}^N. \tag{25}$$

Under which conditions the long-run movements in PC can be driven mainly by shocks to IST? Note that if there exists a consumption-specific technology shock (i.e., $B_{11}=1+B_{21}$) with a positive spillover effect ($B_{21}>0$), its direct impact on PC would be negative, because an improvement in consumption-specific technology tends to reduce the relative price of consumption to investment. Thus, a positive correlation of the two long-run shocks, as we show below, implies that the permanent IST shock plays a dominant role in the long-run fluctuations in PC.

We now explore the validity of our measure of the importance of permanent IST shocks for long-run fluctuations in aggregate TFP, that is, the correlation of the two long-run shocks, when technology spillover may originate from both sectors. Equations (24) and (25) imply that the correlation coefficient between the two long-run shocks can be expressed as follows:

$$\rho\left(\varepsilon_t^{PC}, \varepsilon_t^{TFP}\right) = \frac{1}{\sqrt{1+\frac{\sigma_{\eta_1^N}^2}{\sigma_{\eta_1^I}^2}\frac{(B_{11}-B_{21})^2}{(B_{22}-B_{12})^2}+\frac{\sigma_{\upsilon_1}^2}{\sigma_{\eta_1^I}^2(B_{22}-B_{12})^2}}\sqrt{1+\frac{\sigma_{\eta_1^N}^2}{\sigma_{\eta_1^I}^2}\left(\frac{F^C}{F^I}\right)^2}} - \frac{1}{\sqrt{1+\frac{\sigma_{\eta_1^I}^2}{\sigma_{\eta_1^N}^2}\frac{(B_{22}-B_{12})^2}{(B_{11}-B_{21})^2}+\frac{\sigma_{\upsilon_1}^2}{\sigma_{\eta_1^N}^2(B_{11}-B_{21})^2}}\sqrt{1+\frac{\sigma_{\eta_1^I}^2}{\sigma_{\eta_1^N}^2}\left(\frac{F^I}{F^C}\right)^2}}. \tag{26}$$

To understand Eq. (26), consider two special cases. First, assume that there is only investment-specific technology. In this case, $B_{22}=1+B_{12}$ and $B_{11}=B_{21}=F^C$. Accordingly, the correlation of the two long-run shocks becomes

$$\rho\left(\tilde{\varepsilon}_t^{PC}, \tilde{\varepsilon}_t^{TFP}\right) = \frac{1}{\sqrt{1+\frac{\sigma_{\eta_1^N}^2}{\sigma_{\eta_1^I}^2}\left(\frac{B_{11}}{F^I}\right)^2}\sqrt{1+\frac{\sigma_{\upsilon_1}^2}{\sigma_{\eta_1^I}^2}}},$$

which is equivalent to Eq. (18), with $\beta \equiv F^I/B_{11}$. It is easy to show that the two arguments in the denominators equal $\Omega_{TFP,\eta_1^I}(k)$ and $\Omega_{PC,\eta_1^I}(k)$, respectively, as $k \to \infty$. Once again, the effect of permanent IST 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, $B_{11}=1+B_{21}$ and $B_{22}=B_{12}=F^I$. Accordingly, the correlation of the two shocks becomes

$$\rho\left(\varepsilon_t^{PC},\varepsilon_t^{TFP}\right)=-\frac{1}{\sqrt{1+\frac{\sigma^2_{\eta_1^I}}{\sigma^2_{\eta_1^N}}\left(\frac{B_{22}}{F^C}\right)^2}\sqrt{1+\frac{\sigma^2_{\upsilon_1}}{\sigma^2_{\eta_1^N}}}}.$$

Similarly, the effect of consumption-specific technology on aggregate TFP depends on the 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 long-run shocks depends on the relative magnitude of the spillover from each sector-specific technology. If the spillover from permanent IST 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 (26) 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 long-run shocks reveals whether permanent IST shocks or shocks to consumption-specific technology dominate the underlying common driving force of TFP and PC.

In summary, we provide a model of technology spillover and establish the linkage between the primitive shocks in the model and the long-run shocks to PC and TFP that can be identified from a VAR approach. Based on this mapping, we show that both the magnitude and the sign of the correlation of these two long-run shocks sheds light on the quantitative importance of the permanent IST shock to long-run TFP fluctuations.

3. Empirical approach

In this section, we would like to identify empirically the two long-run shocks constructed in our model: one shock accounting for the long-run movements in aggregate TFP and the other accounting for the long-run movement in the inverse of the relative price of investment. Different from previous empirical studies in VAR literature, our theory suggests that the two long-run shocks we identify could be a combination of various primitive shocks.

An approach that satisfies our goal of identification is the Maximum Forecast Error Variance Approach. The identification scheme is fairly standard: we adopt the approach in Francis et al. (2012), a variant of Uhlig's (2004) approach, to extract the shock that best explains the FEV at a long, and finite horizon for a given target variable i, where i is either TFP or PC. According to our model, long-run fluctuations in both aggregate TFP and the inverse of the relative price of investment could be driven by a common shock, that is, a permanent innovation to the investment-specific technology. Therefore, we use this approach sequentially, rather than simultaneously, to identify these two long-run shocks.

Another advantage of the MFEV approach is its flexibility in the treatment of the idiosyncratic and common stochastic trends of the variable of interest. Note that the processes of TFP and PC may contain both common and idiosyncratic stochastic components. Since our focus is to quantify the effect of the common component as measured by the correlation of the two long-run shocks, we would like to avoid taking a stand on the cointegration relationship between TFP and PC. The MFEV approach satisfies this purpose, as it does not require imposing the long-run relationship a priori.

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

$$\mathbf{Y}_t=C(L)\mathbf{u}_t, \tag{27}$$

where Y_t is a $m\times 1$ vector of variables at time t, $C(L)=I+\sum_{i=1}^{\infty}C_iL^i$ is a polynomial in the lag operator L, and $\mathbf{u}_t$ 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 the reduced-form innovations and structural shocks:

$$\mathbf{u}_t=A\tilde{\boldsymbol{\varepsilon}}_t, \tag{28}$$

where $\tilde{\boldsymbol{\varepsilon}}_t$ denotes the vector of empirically identified long-run shocks. The key restriction on A is that it satisfies $\Sigma=E\left[A\tilde{\boldsymbol{\varepsilon}}_t\tilde{\boldsymbol{\varepsilon}}_t'A'\right]=AA'$. This restriction is not sufficient to identify A, since for any matrix A there exists an alternative matrix $\tilde{A}$, such that $A=\tilde{A}Q$, where Q is an orthonormal matrix. This alternative matrix $\tilde{A}$ maps $\mathbf{u}_t$ into another mutually orthogonal structural shock $\tilde{\tilde{\boldsymbol{\varepsilon}}}_t$, $\mathbf{u}_t=\tilde{A}\tilde{\tilde{\boldsymbol{\varepsilon}}}_t$. 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 best explains the fluctuations in y_i at the forecast horizon k, we can identify such a shock by finding a column q_1 of Q that explains the FEVs of variable y_i in Y_t at the forecast horizon k. Specifically, we solve the following maximization problem, given the Cholesky decomposition of Σ, $\tilde{A}$:

$$q_1=\text{argmax}\, q_1'Sq_1\equiv q_1'\left[\sum_{l=0}^{k}\tilde{A}'C_l'(e_ie_i')C_l\tilde{A}\right]q_1 \tag{29}$$

subject to

$$q_1' q_1 = 1 \tag{30}$$

where S is the variance of the k-step ahead forecast error of the ith variable in Y_t.[22] The constraint (30) guarantees that q_1 is a unit-length column vector that belongs to an orthonormal matrix. Uhlig (2004) shows that this problem can be written as a quadratic form in which q_1 is the eigenvector associated with the largest eigenvalue of the matrix S.

Note that the MFEV approach only identifies the shock that best explains the long-run fluctuation of the variable in interest. This implies that the shock identified under this approach may not be able to account for all the forecast error variance of the target variable. In Appendix 7.5, we show that in this case the correlation of the two long-run shocks identified under the MFEV approach can still uncover the importance of IST spillover. Therefore, if our identified empirical shocks can account for most of the FEV of the corresponding variables in the long run, as we show later in Section 5, the correlation of the two empirically identified shock can still serve as a good measure of the quantitative importance of permanent IST shocks to long-run fluctuations in TFP.

An alternative strategy to identify the long-run shocks, which has often been used in the literature, is the long-run (LR) identification as proposed by Blanchard and Quah (1989). Specifically, a transformation of the moving average representation of the reduced-form VAR gives

$$\mathbf{Y}_t = C(L)A\tilde{\boldsymbol{\varepsilon}}_t.$$

The LR identification imposes restrictions on the effect of the jth shock on the ith variable at an infinite horizon. This is implemented through restrictions on the long-run cumulative matrix $C(1)A$. So, for an $I(1)$ variable such as PC or TFP entering the VAR in *differences*, the neutrality implied by the LR approach suggests that $[C(1)A]_{i,j} = 0$. In other words, the level of variable i is not affected in the long-run by the structural shock j. Nonetheless, this approach would be inconsistent with our theory, as it would eliminate any potential common component between the PC and TFP series. Therefore, we choose to not adopt this approach to identify the two long-run shocks as constructed in our model.

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 our identified 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 et al. (2011). The denominator is the National Income and Product Accounts (NIPA) deflator for durable consumption and private investment. However, Gordon (1990) and Commins 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.[23]

The series of aggregate TFP growth is taken from Fernald (2012), measured as the growth rate of business-sector TFP.[24] 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

$$\Delta \log TFP_t^C = \Delta \log TFP_t - w^I \Delta \log P_t^C / P_t^I, \tag{31}$$

with the values of w^I taken from Fernald (2012).[25] 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

[22] 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.

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

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

[25] Note that Eq. (31) 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.

domestic investment.[26] Hours H is per capita hours worked in the nonfarm business sector.[27] 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 stock index is converted to a quarterly frequency by taking the average of the monthly stock index over each quarter. The price deflator is the price index for gross value added in the non-farm business sector, taken from the Bureau of Economic Analysis (Table 1.3.4). The data for the consumer confidence index, federal funds rate, and CPI index are from Beaudry et al. (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 estimating the system in levels will produce consistent estimates of impulse responses and is robust to cointegration of unknown forms.[28] In Section 5.2.4, however, we show that our results are very robust when we estimate a vector error correction model (VECM). According to standard likelihood methods, three or four 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 three-lag specification. We compute the error band with residual-based bootstrap, as in Kilian (1998).

Since our goal is to identify the shock that best explains the long-run movement of PC or TFP, we would like to choose a forecast horizon k under MFEV that is sufficiently long. How do we choose the appropriate forecast horizon k? Empirically, for small samples, k cannot be too large. Otherwise, misspecification bias would rise as the identification horizon increases.[29] Therefore, we would like to choose the smallest forecast horizon, $\widehat{k}$, under MFEV such that when $k \geq \widehat{k}$, the MFEV approach essentially identifies the same long-run shock to the variable in question. Specifically, our strategy is as follows: (1) We identify the TFP shock under various horizons $k=40, 60, 80, 100$, and 120; (2) We compute the correlation among the identified shocks to TFP; (3) We choose the smallest forecast horizon $\widehat{k}$ under MFEV such that the correlation coefficient of shocks to TFP identified under various forecast horizons $k \geq \widehat{k}$ is close to 1 and has a small confidence band. Our results suggest that, when $k \geq 80$, the correlation coefficient between the identified TFP shocks is close to 1 for both the median and the boundaries of the 16–84 percent confidence band.[30] Hence, we pick $\widehat{k} = 80$ for our benchmark specification. Such a forecast horizon is consistent with the empirical diffusion lag of a new technology. 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. In Section 5.2.5, we will examine the robustness of our results when the two long-run shocks are identified under alternative forecast horizons.

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, a split sample, and alternative empirical specifications. Finally, we explore the correlation of shocks to TFP and PC identified under 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

Fig. 1 displays the IRFs of various variables to the shock to PC (solid line), with 16to 84 percent posterior coverage intervals shaded in gray. To compare, we also plot their counterparts to the shock to TFP (dashed line). What is striking is that the IRFs of all the variables to the two identified long-run shocks are surprisingly close to each other. Specifically, under both shocks, the response of PC—the inverse of the relative price of investment—is close to zero on impact. After that, PC gradually increases, and then peaks at 33 quarters at 0.7 percent higher than its pre-shock value. In regards to TFP, we see that the initial responses of TFP to both shocks are negative within the first nine quarters. Such an initial negative TFP response suggests that, in the short run, the cost of adopting IST by firms in the consumption sector may dominate its direct

[26] Our main results about the quasi-identity of the two identified shocks still hold if investment is measured as the per capital value of the real fixed private domestic investment.

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

[28] Fisher (2010) finds that invalid assumptions concerning common trends may produce misleading results.

[29] See Francis et al. (2012) for a detailed discussion.

[30] We also conducted similar exercise for PC and find that the smallest forecast horizon for identified long-run shocks PC to be essentially the same is 80 quarters.

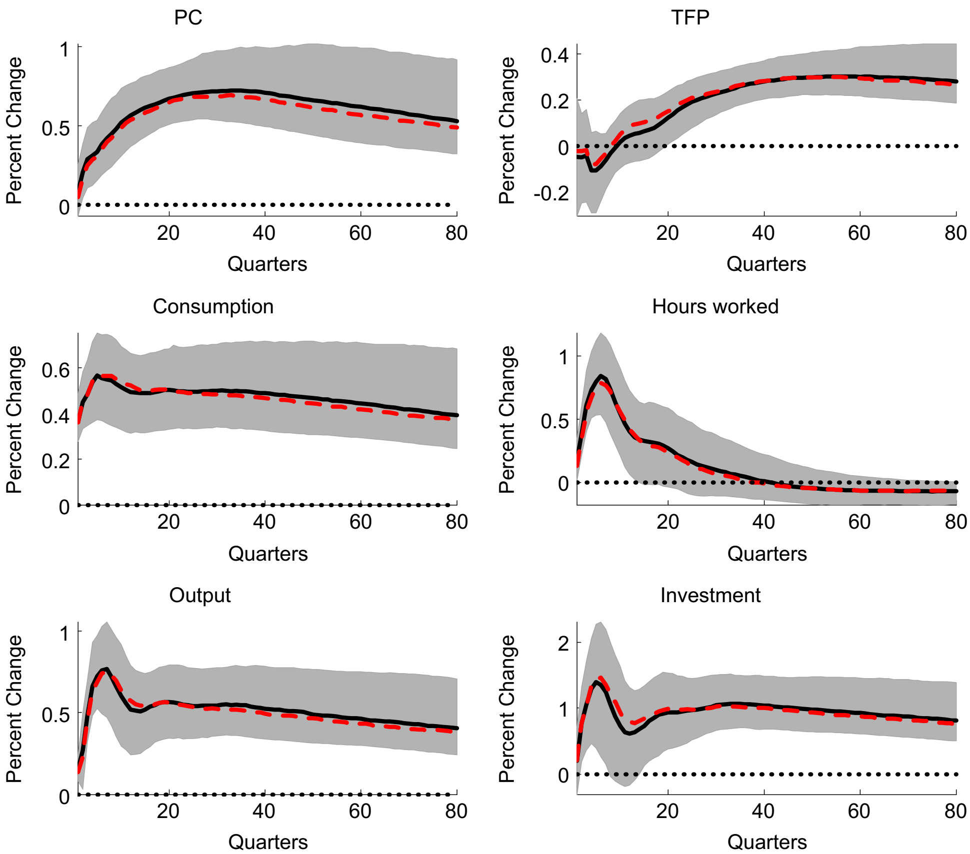

Fig. 1. Impulse responses to shocks to PC and TFP in the baseline specification. *Note*: IRFs to the shock to PC (solid black line) and TFP shock (dashed red line) in the six-variable system with the forecast horizon $k=80$. The shaded gray area represents the 16-percent and 84-percent quantiles of the empirical distribution of the IRFs in the identification of the shock to PC. The distribution is the bootstrapped impulse responses obtained through the residual-based resampling with 1000 replications. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

benefit.[31] From the 9th quarter on, TFP steadily increases and, in the long run, the shock to PC seems to have a permanent positive effect on TFP. Such a pattern is puzzling from the viewpoint of the standard business cycle theory, but is consistent with the response of aggregate TFP to the permanent IST shock as implied by Eq. (11). In particular, the gradual increase of TFP to a permanently higher level suggests that the shock to PC captures a slow diffusion process of general purpose technology. Furthermore, the positive comovement of PC and TFP in the long run in response to the shock to PC is consistent with the spillover from the permanent IST shock to the consumption-sector TFP, rather than from the opposite direction.

Consider now the macro variables. We see that the IRFs of all macro variables to these two shocks are hump-shaped.[32] Moreover, consumption significantly increases on impact. This suggests that consumer confidence or sentiment, triggered by expected future TFP increase, plays some role in the transmission of technology shocks into consumption in initial periods.[33] 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 in the long run, apart from hours worked, which converge to the initial level after the peak, all other variables converge to a new long-run level. This pattern is consistent with our model's prediction that shocks to embodied technology have permanent effects.

The similarity of the two identified shocks is further confirmed by the inspection of the forecast error variance decomposition shown in Fig. 2. We see that the shares of the FEVs of both PC and TFP attributable to these two identified shocks are quantitatively similar. Specifically, on impact, both shocks explain little variation in PC. Over time, however, the FEV of PC attributable to the shock to either PC or TFP increases monotonically. In particular, the shock to TFP alone

[31] The initial negative response of aggregate TFP to the shock to PC is consistent with the findings of Basu et al. (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. Similarly, McGrattan and Prescott (2010) show that intangible investment, such as R&D investment and investment in building organization, is crucial in understanding the boom in the 1990s despite a modest and delayed increase in measured aggregate TFP.

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

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

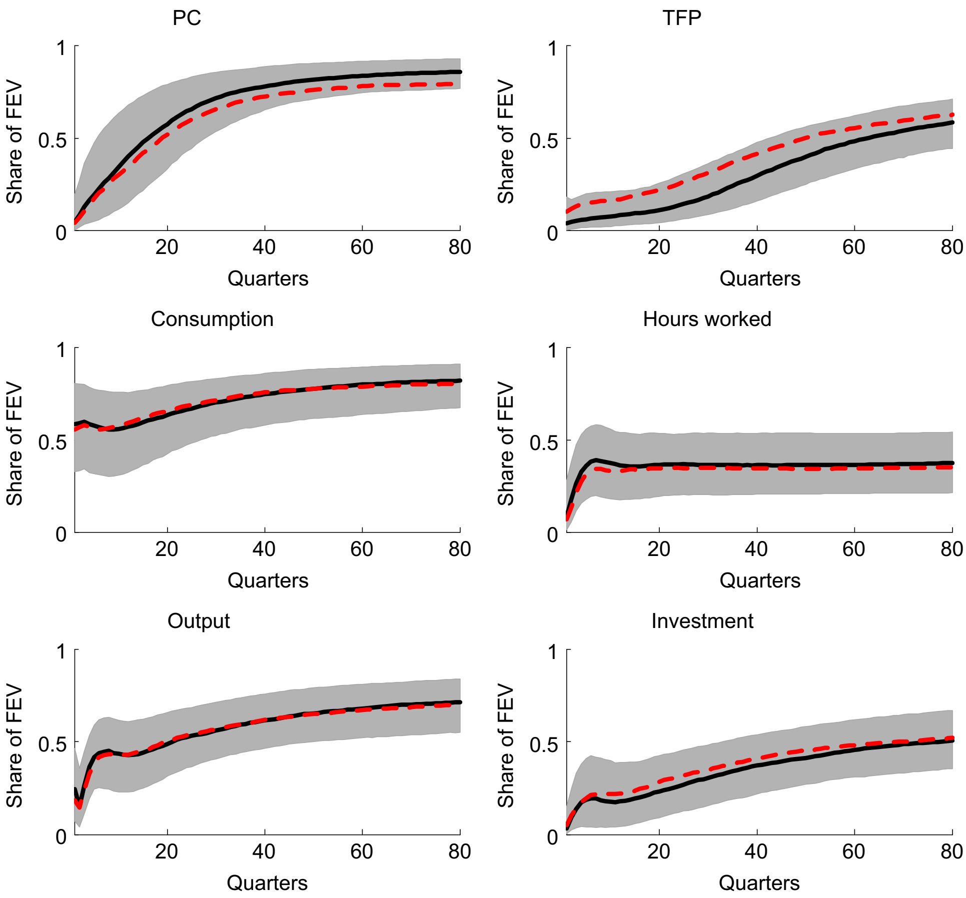

Fig. 2. Share of the FEV decomposition attributable to shocks to PC and TFP in the baseline specification. *Note*: Forecast error variances (FEVs) to the shock to PC (solid black line) and the TFP shock (dashed red line) in the six-variable system with the forecast horizon $k=80$. The shaded gray area represents the 16-percent and 84-percent quantiles of the empirical distribution of the FEVs in the identification of the shock to PC. The distribution is the bootstrapped FEVs obtained through the residual-based resampling with 1000 replications.

Table 1
The share of the FEVs attributable to the shock to PC in the baseline specification.

Variable	$k=0$	$k=4$	$k=8$	$k=16$	$k=40$	$k=80$
PC	0.0453	0.1644	0.2855	0.4993	0.7791	0.8591
TFP	0.0389	0.0580	0.0694	0.0939	0.2964	0.5850
Consumption	0.5856	0.5860	0.5582	0.6062	0.7475	0.8213
Hours	0.0869	0.3273	0.3842	0.3552	0.3630	0.3744
GDP	0.2441	0.3642	0.4500	0.4504	0.6166	0.7145
Investment	0.0331	0.1726	0.1844	0.2002	0.3711	0.5043

Note: The coefficients are obtained from computing the FEVs in the six-variable system with the forecast horizon $k=80$. 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 shock to PC.

contributes to more than 70 percent of the fluctuations in PC 40 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 permanent IST 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 40 percent of TFP fluctuations for forecast horizons beyond 50 quarters. This suggests a slow diffusion and spillover process of IST innovations. As a final remark, our identified shocks to TFP (and PC) under the MFEV approach can account for 63% (86%) of the FEV of TFP (PC) at 80 quarters. This suggests that the two empirically identified shocks under MFEV are good proxy for the long-run shocks to PC and TFP as constructed in our theory.

Turning to the macro variables, both shocks can account for about 60 percent of the FEV of consumption at business cycle frequencies. Moreover, both shocks are important for hours and output fluctuations at business cycle frequencies, explaining

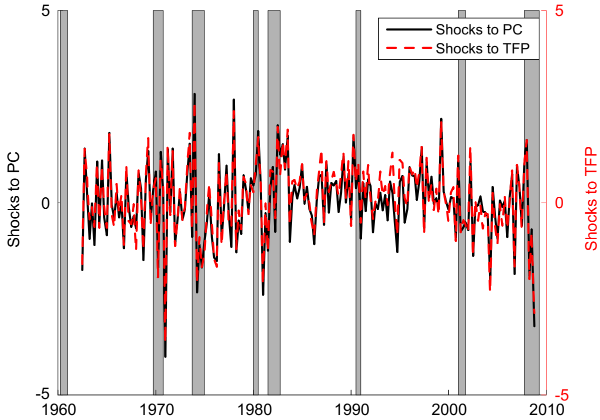

Fig. 3. Time series of the identified shocks to PC and TFP and U.S. recessions. *Note*: The time series of the shocks to PC and TFP are obtained from the six-variable VAR system with the forecast horizon $k=80$. The plotted data correspond to the shock series that yield the median of the distribution of bootstrapped correlations obtained through the residual-based resampling with 1000 replications. The shaded areas represent periods of recessions as dated by NBER.

about 40 percent of their FEVs eight quarters ahead. By contrast, the fluctuation of investment attributable to the 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, technological improvements start to play an important role in investment variations. Table 1 summarizes the FEV coefficients of various variables attributable to the shock on PC at different time horizons.

To quantify the correlation of these two identified shocks, we compute the median and the 16–84 percent confidence band from the distribution of their correlation coefficient across bootstrapped draws.[34] Fig. 3 plots the time series of the identified shocks to TFP and PC that yield the median of the distribution of correlation, 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 median correlation of these two shocks is as high as 0.9690, with a 16–84 percent confidence interval of [0.8072 0.9940].[35] This quasi-identity of the two identified shocks provides further support that the permanent IST shock is one main primitive shock underlying the long-run variations of both aggregate TFP and the relative price of investment.

We now quantify the magnitude of the spillover effect of the permanent IST shock. Our empirical findings suggest that the permanent IST 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 shock to PC. Since Eqs. (13) and (15) only hold asymptotically, we choose a sufficiently long horizon, $k=80$, to compute $\Omega_{TFP,\eta_1^I}(k)$ and $\Omega_{PC,\eta_1^I}(k)$. Then, with the estimated variances of the shocks to TFP and PC, Eq. (19) gives $\beta=0.8233$.[36] 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 magnitude of IST spillover effect, as $\alpha=\beta-w^I=0.6133$. Comparing the value of α with w^I, we conclude that the spillover effect plays the key role in the transmission of the permanent IST shock to long-run TFP fluctuations.

Finally, it is important to check whether our identified shocks capture the impact of other prominent macroeconomic shocks. To address this concern, we compute the correlation between our identified 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.[37]

[34] Specifically, after estimating the VAR, we conduct residual-based resampling with 1000 replications. For each simulation, we identify the shocks to PC and TFP and compute the correlation between the two. We then compute the median and the 16–84 percent confidence band from the distribution of correlations across bootstrapped draws.

[35] Throughout this paper, the correlation coefficient we report is the median correlation from the distribution of correlations across bootstrapped draws, unless otherwise mentioned.

[36] Specifically, the FEVs of TFP and PC attributable to the shock to PC at the horizon of 80 quarters are 0.5850 and 0.8591, respectively; and the variances of the shocks to PC and TFP are 0.9654 and 0.9609, respectively.

[37] 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.

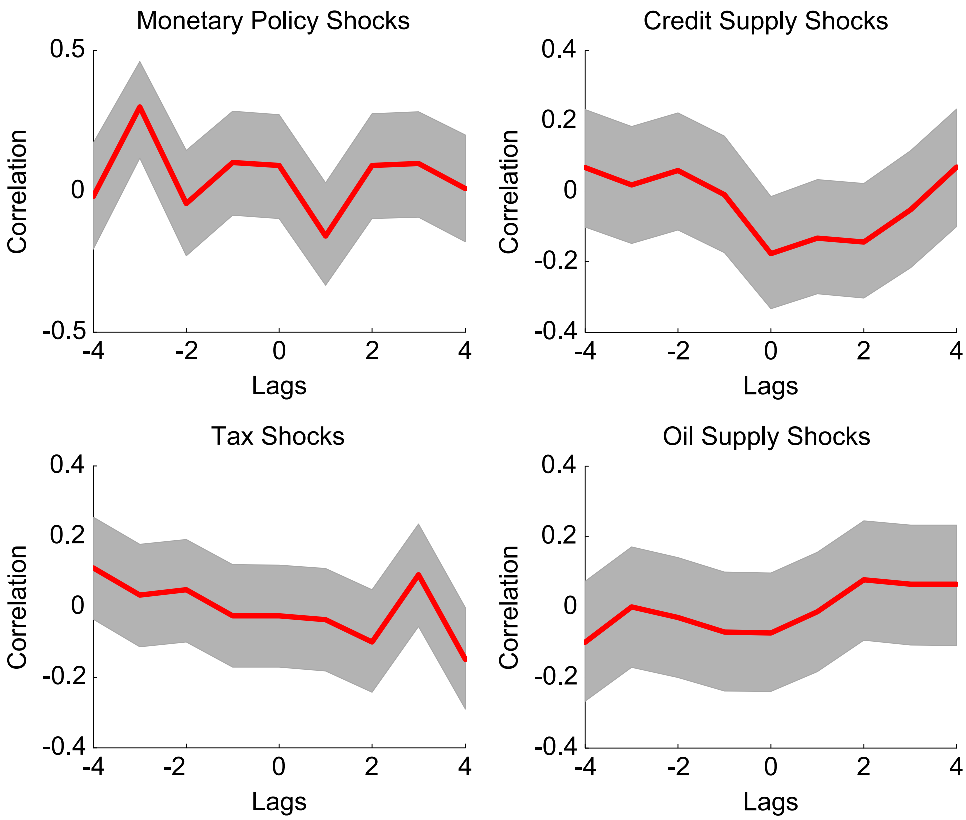

Fig. 4. Cross-correlation between the Shocks to PC and Leads/Lags of Other Macroeconomic Shocks. *Note*: The data for the monetary policy shock are taken from Romer and Romer (2004). The data for the credit supply shock are the shock to the excess bond premium identified from the VAR exercise in Gilchrist 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.

The results are presented in Fig. 4 where the correlation between the 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 -0.1862 (credit supply shocks).[38] Thus, we argue that the main results of the paper are not explained by these other macroeconomic shocks.

5.1.2. Large VAR systems

We next identify the two long-run 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 shed light on the transmission mechanism of permanent IST shocks into the U.S. business cycles.

Fig. 5 reports the IRFs in the VAR system with stock prices. Again, for all variables, the IRFs to the two long-run 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 0.9705. Interestingly, stock prices respond positively to both 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 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. In contrast, 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.[39] 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

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

[39] Christiano and Fisher (2003) obtain this negative comovement in a model with capital adjustment cost, when both a permanent investment-specific technology 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 technology shock represents a positive supply shock to investment goods and, thus, drives down the relative price of investment.

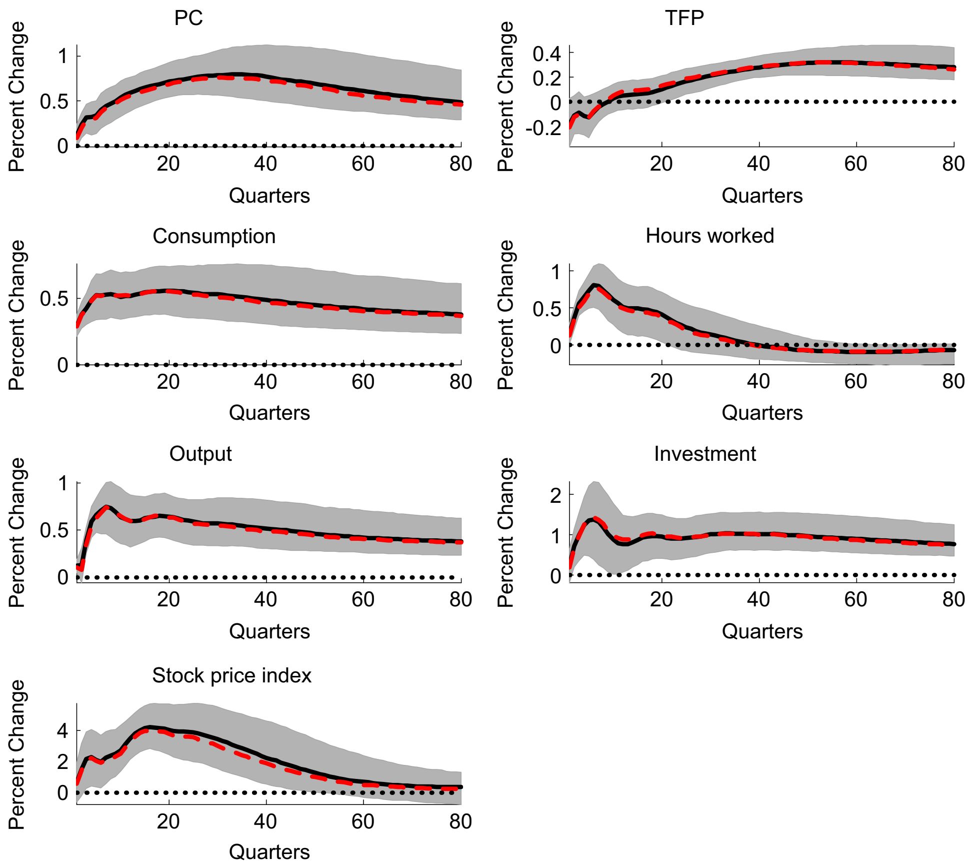

Fig. 5. Impulse Responses to Shocks to PC and TFP in the Larger System with Stock Prices. *Note*: Impulse responses to the shock to PC (solid black line) and the TFP shock (dashed red line) in the seven-variable system with the forecast horizon $k=80$. The shaded gray area represents the 16-percent and 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 1000 replications.

Table 2
The correlation coefficients of the shocks to TFP and PC in larger VAR systems.

Additional variable	Correlation coefficient
Stock price	0.9705
Consumer confidence	0.9695
CPI Inflation & FFR	0.9665

Note: The coefficient represents the correlation between the identified shock to PC and the TFP shock in the larger systems with $k=80$. The left column refers to the additional variables added into the baseline specification. The correlation coefficient in this table is the median from the distribution of bootstrapped correlations obtained through the residual-based resampling with 1000 replications.

relative price of investment via an increase in the supply of investment goods, whereas its impact on aggregate productivity in the long run 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 long-run shocks is 0.9696 and consumer confidence rises on impact. This suggests a potential channel for IST innovations to transmit into the macroeconomy, by affecting consumer sentiment that is based on anticipated long-run movements in aggregate productivity.

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. Fig. 6 reports the IRFs to the two long-run shocks. We see that, again, our main findings hold with the addition of nominal variables. The correlation of the two long-run shocks is 0.9665. Moreover, the inflation rate drops on impact, suggesting that our identified shocks capture a supply shock.

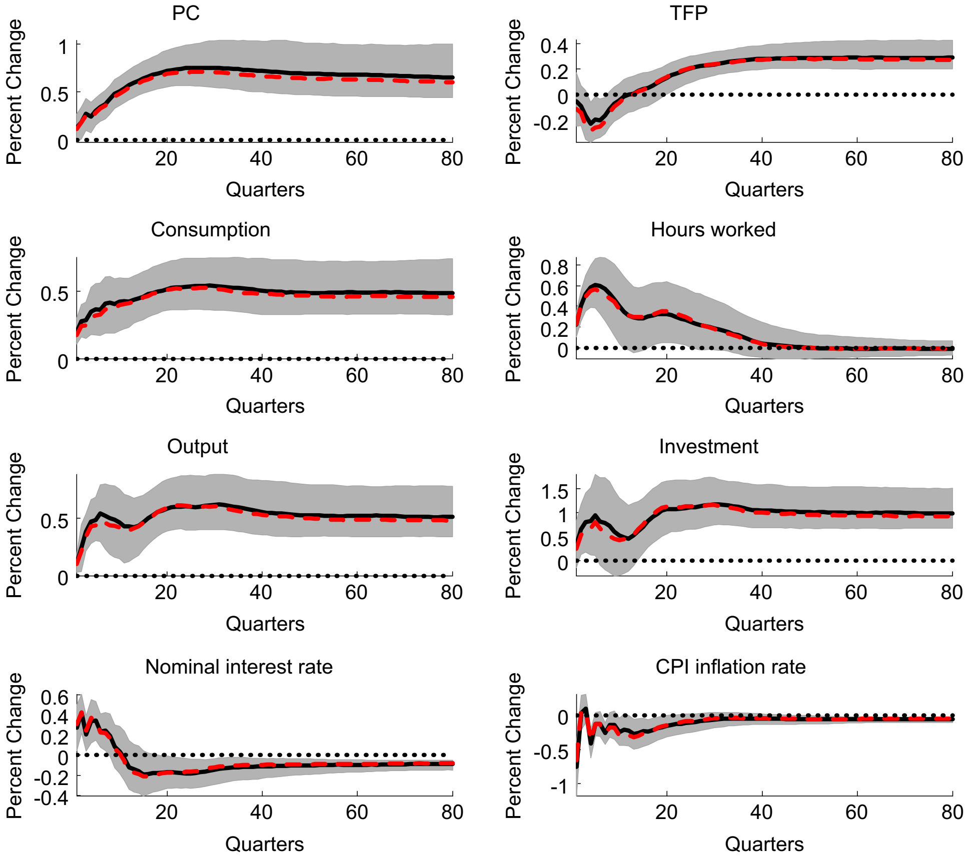

Fig. 6. Impulse Responses to Shocks to PC and TFP in the Larger System with Nominal Variables. *Note*: IRFs to the shock to PC (solid black line) and the TFP shock (dashed red line) in the eight-variable system with the forecast horizon $k=80$. The shaded gray area represents the 16-percent and 84-percent 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 1000 replications.

To summarize, our findings about the high correlation of the two identified shocks suggest that the permanent IST shock is one main driver of long-run movements in aggregate TFP. Such a linkage, by affecting consumer confidence, may provide new insights for permanent IST shocks to transmit into the macroeconomy.

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 and VAR specifications, and under a split sample. After that, we check the robustness of our results under a VECM specification. Finally, we provide a robustness check of our results under alternative forecast horizons under MFEV.[40]

5.2.1. TFP of the consumption sector

According to our theory, the high correlation between the two identified 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 Eqs. (13) and (18) 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 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 permanent IST shock.

[40] We have also checked the robustness of our results with data on a “corrected” measure of PC as the ratio of the raw data on PC to the data on the wedge between PC and IST, constructed according to Eq. (A.7) in the Appendix. And our main findings on both the high correlation of the two long-run shocks and the importance of shocks to PC in explaining the FEV of aggregate TFP in the long run still hold. The details of the results are available upon request.

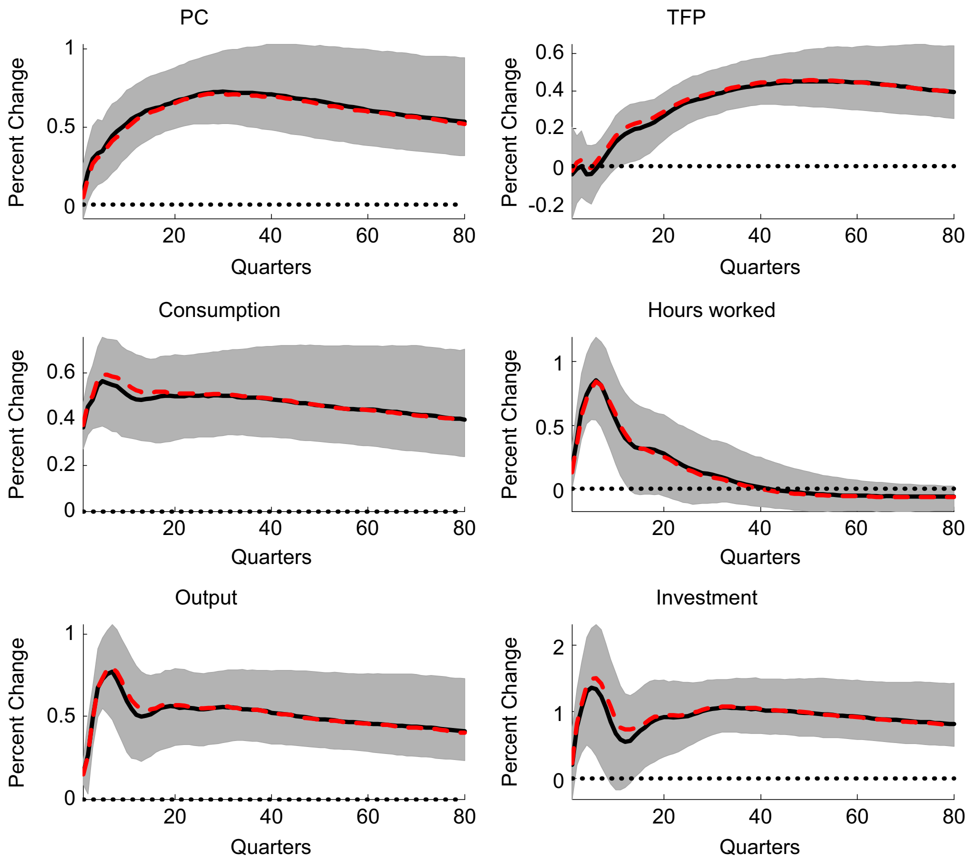

Fig. 7. Impulse Responses to Shocks to PC and TFP in the System with Consumption-sector TFP. *Note*: IRFs to the shock to PC (solid black line) and TFP shock (dashed red line) in the six-variable system with the forecast horizon $k=80$. The shaded gray area represents the 16-percent and 84-percent quantiles 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 1000 replications.

Fig. 7 reports the IRFs of various variables to these two identified shocks with a TFP series of the consumption sector.[41] Again, we see that the IRFs of all variables to these two identified long-run shocks are very similar. In particular, TFP of the consumption sector exhibits a similar IRF to the aggregate TFP shown in Fig. 1. The correlation coefficient between these two identified shocks is 0.9874. 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 Fig. 8, the IRFs of all variables to the two long-run shocks are very close to their counterparts in our baseline system. Accordingly, the correlation coefficient of these two identified shocks is 0.9474.[42]

5.2.3. *With different lags and specifications*

Our results are robust to different lags and alternative VAR specifications. Using three lags in the six-variable VAR system, we obtain a correlation coefficient of the two shocks of 0.9611. Also, we obtain a correlation coefficient of 0.9552 between the two identified long-run shocks in a VAR specification that includes the federal fund rate, the term spread, and other nominal variables. Table 3 summarizes the correlation coefficients of the two identified shocks under these various robustness checks.

[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.

[42] We also adopt the GCV deflator for equipment and software in our robustness check. The correlation between identified shocks to PC and TFP is, again, very high at 0.8333.

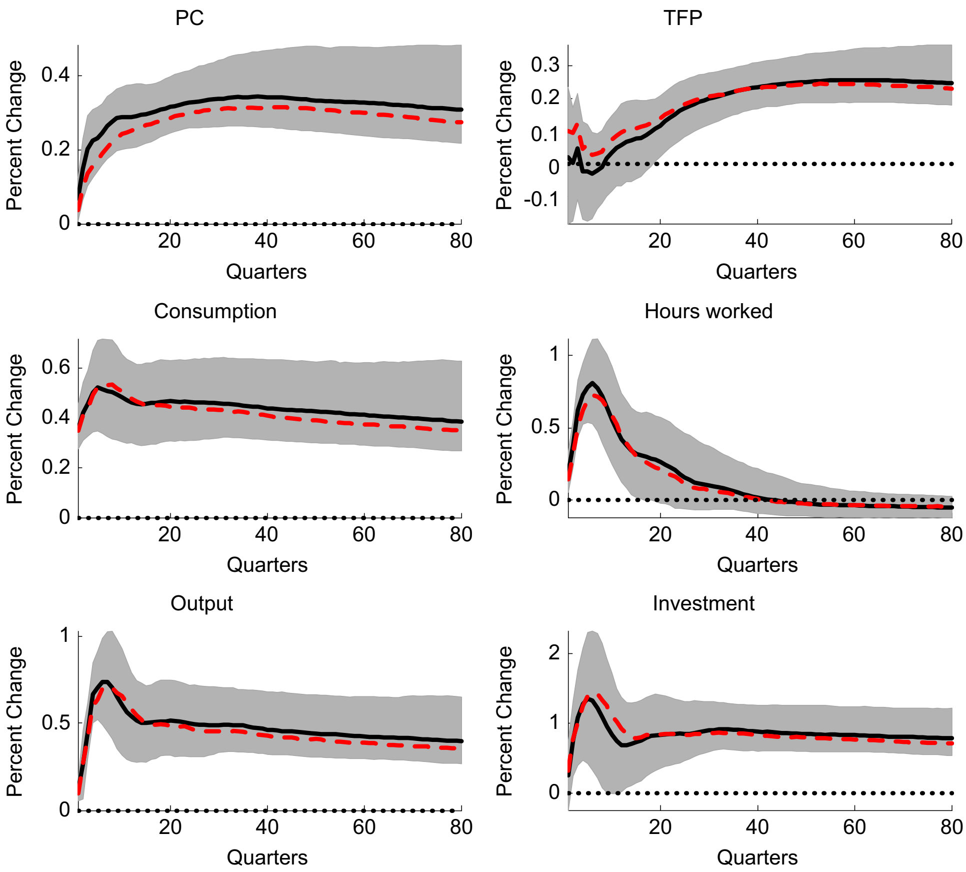

Fig. 8. Impulse Responses to Shocks to PC and TFP in the System with GCV investment Deflator. *Note*: IRFs to the shock to PC (solid black line) and TFP shock (dashed red line) in the six-variable system with the forecast horizon $k=80$. The shaded gray area represents the 16-percent and 84-percent quantiles 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 1000 replications.

Table 3
Robustness checks of the correlation coefficients of the shocks to TFP and PC.

Scenarios	Correlation coefficient
GCV deflator	0.9474
Consumption TFP	0.9874
Three lags	0.9611
Term spread	0.9552

Note: "GCV Deflator" refers to the robustness check in which we replace the NIPA investment deflator with the GCV Deflator. "Consumption TFP" refers to the robustness check in which aggregate TFP is replaced with the TFP of the consumption sector. "Three Lags" refers to the robustness check in which we adopt three lags in a six-variable VAR. "Term Spread" refers to the robustness check in which we adopt the VAR system as in Kurmann and Otrok (2013). The correlation coefficient in this table is the median from the distribution of bootstrapped correlations obtained through the residual-based resampling with 1000 replications.

5.2.4. A split sample

Both Fisher (2006) and Justiniano et al. (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: 1954:Q3 to 1981:Q4 and 1982:Q1 to 2008:Q4.[43]

[43] We push back the starting date of the first subsample from 1961:Q3 to 1954:Q3 to get a similar number of observations as the second subsample.

Table 4
Results from the estimation of a VECM.

Number of cointegrating relationships	Correlation coefficient	Share of FEV of TFP attributable to the shock to PC at the horizon $k=80$
2	0.8294	0.4714
3	0.9519	0.5958
4	0.9763	0.5794

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 shock to PC and the TFP shock are identified under the MFEV of the corresponding variable in levels with the forecast horizon at $k=80$. The correlation coefficient in this table is the median from the distribution of bootstrapped correlations obtained through the residual-based resampling with 1000 replications.

Table 5
The correlation coefficient of the shocks to TFP and PC identified under alternative forecast horizons.

Forecast horizon	Median	Confidence interval
$k=60$	0.9032	[0.5328 0.9821]
$k=80$	0.9690	[0.8072 0.9946]
$k=100$	0.9844	[0.8564 0.9978]
$k=120$	0.9883	[0.9178 0.9983]

Note: The correlation coefficients are obtained from extracting the shocks to TFP and PC in the six-variable system with the forecast horizon k. Both the median and the 16–84 percent confidence band are obtained from the distribution of bootstrapped correlations obtained through the residual-based resampling with 1000 replications.

Our results suggest that the two identified shocks are highly correlated under both subsamples. Specifically, in the first sub-sample, the correlation of the two news shocks is 0.9301, while in the second sub-sample it is 0.9364. Moreover, in both sub-sample around 60 percent of the share of the FEV of TFP is attributable to the identified PC shock. Overall, the main findings of the paper are robust to the presence of a structural break in the PC series.

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).[44] It is well-known that cointegration test results vary greatly in terms of the number of cointegration relationships and are also known to have small power. According to our theory, aggregate output, consumption and investment are cointegrated. Moreover, with IST spillover, aggregate TFP and the inverse of the relative price of investment might be cointegrated. Therefore, we impose two, three and four random cointegration relationships in the estimation of the VECM. In other words, we do not restrict that the PC and TFP series be cointegrated. This is because this constraint would imply a correlation coefficient of one for the two long run shocks, thus invalidating the use of such measure to quantify the importance of IST innovations for long-run TFP fluctuations. We recover the associated vector autoregression using the estimated coefficients obtained from the VECM. Then, we identify the relevant long-run shocks—a shock to PC or TFP—as the innovation that accounts for the FEVs of the level of PC or TFP at a horizon of $k=80$.

The results are summarized in Table 4. As the table indicates, the two long-run shocks identified under the VECM remain highly correlated for various cointegrating relationships.[45] Moreover, the identified 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 finding about the high correlation of the two empirically-identified shocks is robust to VECM specifications.

5.2.6. *Alternative forecast horizons*

So far, our long-run shocks are identified by maximizing the FEVs of the corresponding variable over the forecast horizon $k=80$. 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 identified shocks measures the importance of the IST shock as general purpose technology only if they capture the long-run fluctuations of TFP and PC, respectively. Therefore, as a further test of our theory, we now explore the robustness of the correlation of the two identified shocks to the forecast horizon chosen under the MFEV approach when it is sufficiently long.

The results are reported in Table 5. Interestingly, we see that, the correlation coefficient of the two identified shocks is robust to the choice of the forecast horizon when it is sufficiently long. For example, when identified to maximize the FEV of the corresponding variable at $k=60$, the median correlation coefficient of the two identified shocks is still as high as 0.9032.

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[44] We follow Lutkepohl (2005) to incorporate stationary variables, such as hours worked, in the model.
[45] Even for one cointegration relationship, the correlation between the two shocks remains as high as 0.7104.

The high correlation of the two empirically identified shocks under various long forecast horizons supports our view that the permanent IST shock is a main source of long-run movements in aggregate TFP.

To summarize, our findings about the quasi-identity of shocks to PC and TFP are robust to alternative TFP series, alternative measures of investment deflators, different lags, adding more variables, a split sample, alternative empirical specifications, and alternative forecast horizons.

6. Conclusion

This paper explores the quantitative importance of investment-specific technology changes in the long-run movement in aggregate TFP. To this end, we construct a two-sector model of technology spillover, in which an IST diffusion process influences aggregate TFP via spillover. We establish the linkage between the primitive shocks in such a model and long-run shocks to PC and TFP that can be identified with a VAR approach. We show analytically that the correlation of these two long-run shocks can be fruitful in distinguishing the quantitative importance of IST innovations in long-run TFP fluctuations.

Empirically, we identify the two long-run shocks sequentially using the MFEV approach. Our main empirical finding using post-war U.S. data is that these two shocks are almost perfectly collinear. The observed dynamics of TFP in response to a shock to the inverse of the relative price of investment closely resembles its counterpart of a TFP shock. Moreover, both shocks can explain a significant, and surprisingly similar, fraction of the fluctuations in consumption, output and hours worked over business cycles. Our findings suggest that embodied technological changes, which are general purpose, are important drivers of long-run movements in aggregate TFP.

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 a channel for U.S. business cycles and asset pricing. Uncovering such a channel might also shed light on why outputs across different U.S. industries co-move together, a key feature of U.S. business cycles.

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Appendix A. Supplementary data

Supplementary data associated with this paper can be found in the online version at http://dx.doi.org/10.1016/j.euroecorev.2015.10.002.

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