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Abstract

The relative-price approach to identifying investment-specific technology shocks is inconsistent with a two-sector model with permanent markup change, consumption-specific technology, or sector-specific factor shares. This paper proposes a new approach by finding the model's long-run properties that link labor productivity and the relative price of investment to sector-specific technology change and nontechnology change and by developing a new Max Share identification strategy to exploit these properties. The identified shocks play a large role in both short- and long-run economic fluctuations. This paper also highlights the implications of a broadly overlooked identity between TFP and aggregate sectoral technology.

Keywords: investment-specific technology; total factor productivity; labor productivity; relative price of investment; structural vector autoregression; Max Share

JEL classification: E22, E32

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1. Introduction

In business cycle studies employing vector autoregressions (VARs), it is repeatedly shown that investment-specific technology shocks play a large role in business cycles (Fisher 2006; Galí and Gambetti 2009; Ben Zeev and Khan 2015).[1] The common identifying assumption developed by Fisher (2006) is that the investment-specific technology shock is the sole source of long-run movements in the relative price of investment.[2] This assumption is not innocuous and many papers, including the above papers themselves, are concerned with the conditions required for it to be valid. First, there must be no long-run change in the markup in the investment-goods sector relative to that in the consumption-goods sector. Second, there must be no technology specific to the consumption-goods sector. Unless these conditions are satisfied, a relative markup change or a linear combination of technology shocks in the two sectors is mislabeled as an investment-specific technology shock. Third, factor shares must be the same between the two sectors. Otherwise, sector-neutral technology shocks that affect both sectors simultaneously or nontechnology shocks push up the price more in the sector with the larger labor share by raising the capital-labor ratio. At least the third condition is not supported by data: the labor share computed using the U.S. input-output tables is higher in the investment-goods sector than in other sectors (Chari, Kehoe, and McGrattan 1997; Valentinyi and Herrendorf 2008; Basu, Fernald, Fisher, and Kimball 2013).

This paper develops a new approach to identifying the investment-specific technology shock that is valid even if these conditions are not satisfied. It exploits two steady-state properties of the two-sector model. The first property is that labor productivity measured in

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[1] The evaluation of Fisher (2006) and Ben Zeev and Khan (2015) is based on estimated impulse responses and forecast error decompositions. Their results are explained in detail in Section 4. Galí and Gambetti (2009) show that the Great Moderation reflected low volatility conditional on investment-specific technology shocks.

[2] More boldly, when implementing model simulations or estimations, numerous papers assume that the parameter of investment-specific technology equals the inverse of the relative price of investment at all times (Greenwood, Hercowitz, and Krusell 1997, 2000; Justniano, Primiceri, and Tambalotti 2011; Schmitt-Grohé and Uribe 2012; Khan and Tsoukalas 2012).

terms of investment goods, where the numerator is nominal output divided by the investment deflator, is affected by technology change in the investment-goods sector, not in the consumption-goods sector, and by nontechnology changes such as a change in the capital tax or markup. This is because an increase in the parameter representing the consumption-goods technology is offset by a decrease in the relative price of consumption. This mechanism is irrelevant to whether the factor shares in the two sectors are equal or not. Kimball (1994) first notes the “consumption-technology neutrality” and this paper is the first to exploit it to identify technology shocks.

The second property is that a specific log-linear combination of labor productivity and the relative price of investment is affected by technology change in the consumption-goods sector, not in the investment-goods sector, and by nontechnology change. The effect of the investment-goods sector’s technology is cancelled out, since the relative price of investment is affected by technology change in both sectors while labor productivity in investment units is affected by technology change only in the investment-goods sector.

These two properties imply that a shock that has a long-run effect on labor productivity in investment units but not on the log-linear combination of labor productivity and the relative price of investment is an investment-specific technology shock, not a sector-neutral technology shock nor a nontechnology shock.

One traditional approach to identifying the shocks that satisfy long-run properties is the long-run restriction identification developed by Shapiro and Watson (1988), Blanchard and Quah (1989), and King, Plosser, Stock, and Watson (1991). However, since Galí (1999) identified technology shocks by assuming that they are the sole source of long-run movements in labor productivity, this approach has been criticized because of difficulties in estimating very long-run horizon parameters and in correctly assuming the order of integration of VAR variables.[3] An alternative, proposed by Barsky and Sims (2011) and Francis, Owyang, Roush, and DiCecio (2014), is the "Max Share" approach, where an identified shock is associated with the maximum forecast-error variance share in a target variable at a long, but finite horizon.[4] While it is free from the problems of the long-run restriction approach, it allows for exploitation of only one steady-state property linked to the maximization. Thus, this paper proposes a "constrained" Max Share approach that allows one to exploit the two steady-state properties explained above. Specifically, the identified shock accounts for the maximum forecast-error variance share in one variable at a pre-specified horizon, subject to the constraint that it accounts for essentially none of the forecast-error variance share in another variable. It is noteworthy that the application of the constrained Max Share is not limited to this paper. For example, Ben Zeev and Pappa (2017) try to identify the U.S. military news shock that best explains future movements in defense spending but has no relation to TFP. For this purpose, they identify the shock that maximizes the difference between its contribution to the forecast error variance share in defense spending and that in TFP. This paper's approach allows for a more straightforward identification.

The focus on labor productivity to identify the technology shock is a return to Galí (1999). Francis, Owyang, Roush, and DiCecio (2014) also identify the shock that explains the maximum forecast-error variance share in labor productivity. A slight, but theoretically important, move away from them is that, for the numerator, this paper measures output in terms of investment goods and does not use real GDP. Since real GDP growth is the weighted average of output growth in the two sectors, its shock is also the weighted average of technology shocks in the two sectors. TFP news shocks identified by Barsky and Sims (2011) and

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[3] See, for example, Christiano, Eichenbaum, and Vigfusson (2003) and Chari, Kehoe, and McGrattan (2008). Fernald (2007) shows that the presence of a low-frequency correlation between labor productivity growth and hours worked per capita, which need not be causal, can significantly distort impulse responses to the shock identified by Galí's (1999) long-run restriction.

[4] For a summary of the differences between the two methods, see Francis, Owyang, Roush, and DiCecio (2014).

Kurmann and Sims (2020) with the Max Share approach also reflect the two types of technology shocks, since their measure of TFP is computed using the chain-aggregate output series.

Applying this paper's approach to the U.S. data, I find that the investment-specific technology shock is the most important source of economic fluctuations in both the short- and long-run. The identified shock has long-run effects on TFP, output, investment, and consumption, consistent with the model. It induces positive business-cycle comovement and plays a large role in business cycles: for example, its contribution to the forecast error variance of output at a horizon of two years is 61 percent and much larger than Fisher's (2006) finding. This paper also shows that the relative-price approach fails to identify the investment-specific technology shock correctly: the shock that best explains future movements in the relative price of investment causes little change in TFP, which is inconsistent with the identity between TFP and the weighted average of sectoral technology.

The results from this paper's approach and the failure of the relative-price approach are robust to using alternative investment and consumption deflators. It is also shown that the shock identified by this paper's approach is not Granger-caused by nontechnology shocks identified by other papers. Further, the investment- and consumption-goods technology series computed by Fernald's (2014, 2015) approach, which exploits TFP and the relative price of investment and seems to be complementary to this paper's approach, move in tandem with labor productivity in investment units and its linear combination with the relative price of investment respectively.

Finally, this paper highlights a broad misunderstanding about covariation between TFP and the relative price of investment. Schmitt-Grohé and Uribe (2011) show that TFP and the relative price of investment are cointegrated and argue that this is evidence of a common stochastic trend shared by sector-neutral and investment-specific technologies. Based on multiple statistical tests, Benati (2014) argues against cointegration but admits the possibility of a common stochastic trend. In contrast, Beaudry and Lucke (2010) and Ben Zeev and Khan (2015) assume that the relative price of investment is affected by investment-specific technology shocks while TFP is not in the short- or long-run. All miss the identity between TFP and the weighted average of sectoral technology. The identity implies that TFP reflects investment-specific technology as well as sector-neutral technology at all times. Further, TFP is positively correlated with the relative price of investment by construction, since the latter is intrinsically linked to investment-specific technology.

This paper proceeds as follows. Section 2 explains the econometric strategy. Section 3 explains the data. Section 4 presents the main results. Section 5 assesses the robustness of the empirical results. Section 6 discusses the relation of TFP to sectoral technology and the relative price of investment. Section 7 concludes.

2. Econometric Strategy

This section proposes a new approach to identifying investment-specific technology shocks by studying the steady-state properties of a model economy and by developing a new Max Share identification strategy that allows one to exploit these properties.

2.1 The Model Economy

This paper’s model consists of two sectors: one produces investment goods and another produces all other goods, referred to as consumption goods in this paper. The assumptions made by the relative-price approach are relaxed in the model, allowing for: (i) numerous nontechnology changes, such as markup and capital tax changes, that affect the relative price; (ii) a technology parameter specific to each sector, rather than a priori sector-neutrality; (iii) factor shares that are different between the two sectors. This paper only requires a Cobb-Douglas production function and a King-Plosser-Rebelo type of utility function, both broadly used in macroeconomic modelling, to have the steady-state properties exploited for identification. No adjustment cost mechanisms are assumed, since this paper focuses on the steady state, where such costs are zero.

2.1.1 Goods Producers

Let I and C be investment and consumption respectively. The final goods are produced from intermediates. The production of final goods is competitive while that of intermediate goods is monopolistically competitive. The production functions for final goods are

$$(1) \qquad I_t = \left[\int_0^1 Y_{I,t}(s)^{\frac{\varepsilon_{I,t}-1}{\varepsilon_{I,t}}} ds\right]^{\frac{\varepsilon_{I,t}}{\varepsilon_{I,t}-1}} \text{ and } C_t = \left[\int_0^1 Y_{C,t}(s)^{\frac{\varepsilon_{C,t}-1}{\varepsilon_{C,t}}} ds\right]^{\frac{\varepsilon_{C,t}}{\varepsilon_{C,t}-1}},$$

where $Y_{j,t}(s)$ denotes the output of firm s in sector j. $\varepsilon_{j,t}$ is larger than unity, not constant, and specific to sector j. Final goods producers solve their profit maximization problems. The aggregate price and the demand for intermediate goods are given by

$$(2) \qquad P_{j,t} = \left[\int_0^1 P_{j,t}(s)^{1-\varepsilon_{j,t}} ds\right]^{1/1-\varepsilon_{j,t}} \quad \text{for } j = I, C \ ,$$

$$(3) \qquad Y_{I,t}(s) = I_t \left[\frac{P_{I,t}(s)}{P_{I,t}}\right]^{-\varepsilon_{I,t}}, \qquad \text{and } Y_{C,t}(s) = C_t \left[\frac{P_{C,t}(s)}{P_{C,t}}\right]^{-\varepsilon_{C,t}},$$

where $P_{j,t}$ is the aggregate price and $P_{j,t}(s)$ is the price of individual intermediate goods.

An intermediate-goods firm solves the nominal cost-minimization problem:

$$\min_{K_{j,t}(s),N_{j,t}(s)} R_t K_{j,t}(s) + W_t N_{j,t}(s)$$

$$(4) \qquad \text{s.t.} \quad \bar{Y}_{j,t}(s) = Z_{j,t} K_{j,t}(s)^{\alpha_j} N_{j,t}(s)^{1-\alpha_j},$$

where R_t and W_t respectively denote the nominal rental rate and nominal wage, which are common to all firms, and $K_{j,t}(s)$ and $N_{j,t}(s)$ respectively denote the capital stock and labor inputs used by firm s. The production function is Cobb-Douglas with sector-specific capital share α_j and sector-specific technology $Z_{j,t}$.

The first-order conditions are

$$(5) \qquad R_t = MC_{j,t}(s) Z_{j,t} \alpha_j \left(\frac{K_{j,t}(s)}{N_{j,t}(s)}\right)^{\alpha_j - 1}$$

and

(6) $$W_t = MC_{j,t}(s) Z_{j,t} (1-\alpha_j) \left(\frac{K_{j,t}(s)}{N_{j,t}(s)} \right)^{\alpha_j},$$

where $MC_{j,t}(s)$ is the nominal marginal cost. Since all firms face common factor prices, the capital-labor ratio $K_{j,t}(s)/N_{j,t}(s) \equiv X_{j,t}(s)$ and the marginal cost are also common in sector j. The capital-labor ratio in each sector is given by

(7) $$X_{I,t} = \frac{\alpha_I W_t}{(1-\alpha_I) R_t}$$

(8) $$\text{and } X_{C,t} = \frac{\alpha_C (1-\alpha_I)}{\alpha_I (1-\alpha_C)} X_{I,t}.$$

Thus, if the factor shares are different between the two sectors, so will the capital-labor ratios be.

Given the demand functions (3), all intermediate firms in sector j choose the following price at the steady state:

(9) $$P_{j,*} = \mu_{j,*} MC_{j,*} \text{where } \mu_{j,*} \equiv \frac{\varepsilon_{j,*}}{1-\varepsilon_{j,*}},$$

where an asterisk denotes the steady state and $\mu_{j,t}$ is the markup in sector j. This equation, together with equations (5) and (8), implies

(10) $$\frac{P_{I,*}}{P_{C,*}} = \frac{1-\alpha_C}{1-\alpha_I} \left[\frac{\alpha_C/(1-\alpha_C)}{\alpha_I/(1-\alpha_I)} \right]^{\alpha_C} \frac{\mu_{I,*}}{\mu_{C,*}} X_{I,*}^{\alpha_C - \alpha_I} \frac{Z_{C,*}}{Z_{I,*}}.$$

Equation (10) shows that the following three conditions must be satisfied for the relative price to coincide with technology in the investment-goods sector in the long-run.

First, there must be no long-run change in the relative markup (i.e. $\mu_{I,*}/\mu_{C,*}$ is constant).

Second, there must be no technology specific to the consumption-goods sector. Otherwise, the relative-price approach misidentifies a linear combination of the two sectors' technology shocks as an investment-specific technology shock. This is the reason why the relative-price approach assumes the following specific forms of technology:

$$(11) \qquad Z_{I,t} \equiv Z_{SN,t} Z_{IS,t} \text{ and } Z_{C,t} \equiv Z_{SN,t},$$

where $Z_{SN,t}$ is sector-neutral technology that is common to the two sectors and $Z_{IS,t}$ is investment-specific technology. Technology in the investment-goods sector is a log-linear combination of the two types of technology and technology in the consumption-goods sector is sector-neutral technology. In this case, the relative technology boils down to investment-specific technology.

Third, the capital share must be equalized between the two sectors to prevent the capital-labor ratio X_I from affecting the relative price, since the capital-labor ratio is affected by sector-neutral technology change and nontechnology change in the long-run. With a difference in the capital share, the price in the sector with the lower capital share (i.e. higher labor share) is pushed up more by a permanent increase in the real wage due to a permanent increase in the capital-labor ratio (see equation (7)).

The data do not support at least the third of the three conditions and indicate that $\alpha_I < \alpha_C$. Basu, Fernald, Fisher, and Kimball (2013), Valentinyi and Herrendorf (2008), and Chari, Kehoe, and McGrattan (1997) compute the sectoral factor shares using the U.S. input-output tables. Essentially all exploit the relationship that factor shares in a sector are the aggregates of factor shares in industry outputs that belong to the sector as intermediate inputs and value added. Basu, Fernald, Fisher, and Kimball's results (2013) indicate that $\alpha_I = 0.29$ and $\alpha_C = 0.34$ on average in the period 1961-2004. Valentinyi and Herrendorf's (2008) results for 1997 are very similar: $\alpha_I = 0.28$ and $\alpha_C = 0.35$. In Chari, Kehoe, and McGrattan's (1997) results for 1987, the difference is larger, with $\alpha_I = 0.31$ and $\alpha_C = 0.39$. Since there are differences not only in the sample period but also in the definition of investment and consumption across these studies, the result that $\alpha_I < \alpha_C$ is robust.[5]

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[5] This paper aggregates Basu, Fernald, Fisher, and Kimball's (2013) results for private equipment and structure investment to compute the capital share in the investment-goods sector. The capital share in the consumption goods sector is computed by using this number and Fernald's (2014) capital share in the total businesss sector. Valentinyi and Herrendorf's (2008) investment includes government investment and their output is GDP. Chari,

2.1.2 Household, Government, and Market Clearing

The household gets utility from consumption and disutility from working and rents capital by purchasing investment goods. The utility maximization problem, where the utility function is of the King-Plosser-Rebelo type, is given by

$$\max_{C_{H,t},N_t} \sum_{t=0}^{\infty} \beta^t \left[\log C_{H,t} - \varphi \frac{N_t^{1+\frac{1}{\eta}}}{1+\frac{1}{\eta}} \right]$$

$$\text{s.t.}\, P_{C,t}C_{H,t} + P_{I,t}I_{H,t} + B_{t+1} = W_t N_t + (1+i_t)B_t + (1-\tau_t)R_t K_t + P_{I,t}\tau_t\delta_t K_t - T_t$$

$$\text{(12)} \qquad \text{and} \quad K_{t+1} = I_{H,t} + (1-\delta_t)K_t,$$

where $C_{H,t}$ is the household's consumption, N_t is labor supply, $I_{H,t}$ is the household's purchase of investment goods, B_t is nominal government bonds, i_t is the nominal interest rate, τ_t is the capital tax rate, δ_t is the depreciation rate, and T_t is a lump-sum tax. The first-order conditions are

$$\text{(13)} \qquad \frac{1}{C_{H,t}} = \lambda_t P_{C,t},$$

$$\text{(14)} \qquad \varphi N_t^{\frac{1}{\eta}} = \lambda_t W_t,$$

$$\text{(15)} \qquad \lambda_t = \beta\lambda_{t+1}(1+i_{t+1}),$$

$$\text{(16)} \qquad \iota_t = \beta\left[\lambda_{t+1}\left\{(1-\tau_{t+1})R_{t+1} + P_{I,t+1}\tau_{t+1}\delta_{t+1}\right\} + \iota_{t+1}(1-\delta_{t+1})\right],$$

$$\text{(17)} \qquad \text{and} \quad \iota_t = \lambda_t P_{I,t},$$

where λ_t and ι_t are Lagrange multipliers.

A key equation representing the consumption-technology neutrality is the equation for the capital-labor ratio in the investment-goods sector, which is given by combining equations (16) and (17), substituting the capital demand equation (5) for the investment-goods sector, and evaluating the resultant equation at the steady state:

Kehoe, and McGrattan (1997) allocate final demand other than private consumption and investment to the two sectors proportionately.

(18) $$X_{I,*} = \left[\frac{\alpha_I Z_{I,*}}{\mu_{I,*}\{(1/\beta - 1)/(1-\tau_*) + \delta_*\}}\right]^{1/(1-\alpha_I)}.$$

Given that $X_{C,*}$ depends only on $X_{I,*}$ as shown by equation (8), this equation shows that capital deepening is caused only by technology improvements in the investment-goods sector and changes in nontechnology parameters. Sector-neutral technology assumed by the relative-price approach also causes capital deepening, since it constitutes $Z_{I,*}$, as shown by equation (11). In contrast, technology improvements only in the consumption-goods sector do not raise capital demand, since they push down the relative price of consumption and do not raise the marginal product of capital measured in terms of investment.[6]

To close the model, this paper derives aggregate production functions by integrating market equilibrium equations for intermediate goods obtained by equating equations (3) and (4). At the steady state, accompanied by no price dispersion, these are

(19) $$I_* = Z_{I,*}X_{I,*}^{\alpha_I}N_{I,*} \text{ and } C_* = Z_{C,*}X_{C,*}^{\alpha_C}N_{C,*} \text{ where } N_{j,t} = \int_0^1 N_{j,t}(s)ds.$$

Market clearing conditions for investment goods, consumption goods, labor, and capital stock are

(20) $$I_t = I_{H,t},\ C_t = C_{H,t} + C_{G,t},\ N_t = N_{I,t} + N_{C,t}, \text{ and } K_t = K_{I,t} + K_{C,t},$$

where $C_{G,t}$ denotes the government's purchases of consumption goods. It is assumed that the government collects taxes and issues bonds to purchase consumption goods. The government's nominal budget constraint implied in this model is

$$P_{C,t}C_{G,t} = B_{t+1} - (1+i_t)B_t + \tau_t(R_t - P_{I,t}\delta_t)K_t + T_t.$$

The monetary policy rule is not specified, since this paper focuses on the steady state conditions.

2.1.3 Identifying Approach

Aggregate output measured in terms of investment goods, denoted by Y_t, is represented by

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[6] This is shown by combining equations (16) and (17), substituting the capital demand equation (5) for the consumption-goods sector, and evaluating the resultant equation at the steady state.

$$(21) \qquad Y_t \equiv I_t + \frac{P_{C,t}}{P_{I,t}} C_t$$

The equation for labor productivity is given by combining this equation and the production functions (19) and substituting the capital-labor ratio equations (8) and (18) and the relative-price equation (10) into the resultant equation at the steady state:

$$(22) \quad \frac{Y_*}{N_*} = Z_{I,*}^{\frac{1}{1-\alpha_I}} \left[\frac{\alpha_I}{\mu_{I,*}\{(1/\beta - 1)/(1-\tau_*) + \delta_*\}} \right]^{\frac{\alpha_I}{1-\alpha_I}} \left\{ \frac{N_{I,*}}{N_*} + \frac{(1-\alpha_I)\mu_{C,*}}{(1-\alpha_{NI})\mu_{I,*}} \left(1 - \frac{N_{I,*}}{N_*}\right) \right\}.$$

In this model, the sectoral share in the labor market is unaffected by technology change at the steady state.[7] Thus labor productivity is determined by parameters for investment-goods technology and nontechnology. The technology parameter in the consumption-goods production function is not in the equation because its change is offset by a change in the relative price of consumption and because it is irrelevant to the steady-state level of the capital-labor ratio. This is Kimball's (1994) consumption-technology neutrality. The first useful property is the following.

Property 1. In the long-run, only technology shocks in the investment-goods sector and nontechnology shocks affect labor productivity measured in terms of investment goods.

Identifying investment-specific technology shocks requires an additional property, since the shocks that have long-run effects on labor productivity in investment units could be nontechnology shocks or, as seen in the technology-mapping equations (11), sector-neutral

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[7] This property is from the assumption of no government purchases of investment goods. It is shown by equating the capital accumulation equation (12) evaluated at the steady state to the investment-goods supply equation (19) and combining the resultant equation with the capital-labor ratio equations (8) and (18) and the market clearing conditions for capital stock and labor inputs (20). If the government increases the purchase of consumption goods at the rate of technology improvements in the consumption-goods production, that is, $C_{G,*}/\left(Z_{C,*}Z_{I,*}^{\alpha_C/(1-\alpha_I)}\right)$ is constant, total labor supply and sectoral labor inputs are also unchanged for technology change at the steady state. This is shown by substituting the consumption equation (13) into the labor supply equation (14) and combining the resultant equation with the labor demand equation, goods supply equation for consumption goods, and market clearing condition, (6), (19) and (20). Even if the government purchases investment goods as well, total labor supply and sectoral labor inputs at the steady state are unchanged for technology change when the government increases investment-goods purchases at the rate of technology improvements in the investment-goods production, that is, $I_{G,*}/Z_{I,*}^{1/(1-\alpha_I)}$, where $I_{G,t}$ denotes government investment, is constant.

technology shocks that simultaneously hit the consumption-goods sector's production function. Thus, this paper purifies the shocks by finding a variable that only technology shocks in the consumption-goods sector and nontechnology shocks affect in the long-run and by constraining identified shocks not to affect such a variable in the long-run. A specific log-linear combination of labor productivity in investment units and the relative price of investment satisfies such a property, since the latter variable reflects technology change in both sectors and can cancel out the effect of technology change in the investment-goods sector in the former variable. This paper specifies its form by combining the relative-price equation (10), the capital-labor ratio equation (18), and the labor productivity equation (22) to eliminate the investment-goods technology parameter:

$$\frac{P_{I,*}}{P_{C,*}}\left(\frac{Y_*}{N_*}\right)^{1-\alpha_C} = \frac{Z_{C,*}}{\Theta_*}, \tag{23}$$

where Θ_* collects nontechnology terms.[8] The labor share, $1\text{-}\alpha_C$, appears because of a difference in the capital deepening effect on each variable: the coefficients on the capital-labor ratio are α_I for labor productivity and $\alpha_C\text{-}\alpha_I$ for the relative price of investment. Fortunately, an estimate of α_C is readily available. The second useful property is the following.

Property 2. In the long-run, only technology shocks in the consumption-goods sector and nontechnology shocks affect the log-linear combination of labor productivity measured in terms of investment goods and the relative price of investment.

The two properties give the identifying assumption that an investment-specific technology shock is a shock that has a long-run effect on labor productivity in investment units but not on the log-linear combination of labor productivity in investment units and the relative price of investment. In order to identify such a shock, this paper develops a constrained Max Share

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[8] Kimball's (1994) consumption-technology neutrality result requires a Hicks-neutral type of technology and a King-Plosser-Rebelo type of utility function, but does not require a Cobb-Douglas production function. This paper uses a Cobb-Douglas production function to derive equation (23).

approach that allows identification of the shock that accounts for the maximum forecast-error variance share in labor productivity in investment units at a long, but finite horizon, subject to the constraint that it accounts for essentially none of the forecast-error variance share in the log-linear combination of labor productivity in investment units and the relative price of investment. The new approach is explained in detail in the next subsection.

Finally, this paper shows that the nominal investment-output ratio, or equivalently the ratio of the quantity of the two goods measured in terms of the same goods, is affected only by nontechnology shocks in the long-run. This is the balanced-growth property of the model and works as a litmus test for assessing whether identified shocks are contaminated by nontechnology shocks or not. The equation for investment per unit of labor input at the steady state is derived by combining the capital-labor ratio equations (8) and (18), the capital accumulation equation (12) evaluated at the steady state, and the market equilibrium condition for capital stock (20):

$$(24)\quad \frac{I_*}{N_*} = \delta\left[\frac{\alpha_I Z_{I,*}}{\mu_{I,*}\{(1/\beta - 1)/(1-\tau_*) + \delta_*\}}\right]^{1/(1-\alpha_I)}\left\{\frac{N_{I,*}}{N_*} + \frac{\alpha_C(1-\alpha_I)}{\alpha_I(1-\alpha_C)}\left(1 - \frac{N_{I,*}}{N_*}\right)\right\}.$$

Note that it is affected by technology in the investment-goods sector, but not by technology in the consumption-goods sector. Dividing this by the labor productivity equation (22) yields

$$(25)\qquad \frac{I_*}{Y_*} = \frac{\alpha_I\delta_*\left\{\frac{N_{I,*}}{N_*} + \frac{\alpha_C(1-\alpha_I)}{\alpha_I(1-\alpha_{NI})}\left(1 - \frac{N_{I,*}}{N_*}\right)\right\}}{\mu_{I,*}\left(\frac{1/\beta - 1}{1-\tau_*} + \delta_*\right)\left\{\frac{N_{I,*}}{N_*} + \frac{\mu_{C,*}(1-\alpha_I)}{\mu_{I,*}(1-\alpha_C)}\left(1 - \frac{N_{I,*}}{N_*}\right)\right\}}.$$

The right-hand side includes no technology term. Thus, if identified shocks are not contaminated by nontechnology shocks, they do not affect the nominal investment-output ratio.[9]

2.1.4 Summary of the Effects of Sectoral Technology Improvements

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[9] Watanabe (2012) identifies the permanent nontechnology shock as the shock that has a permanent effect on the nominal investment-output ratio and studies its role in G7 countries' business cycles.

It is useful to summarize the theoretical effects of the sectoral technology improvements that can be compared with empirical results. Though both long-run change and no long-run change in labor inputs are possible in theory, the U.S. data support the latter, as will be shown later. Given this, permanent technology improvements in the investment-goods sector cause permanent increases in output and investment. The same is true for consumption, as implied by the capital-labor ratio equations (8) and (18) and the consumption-goods supply equation (19). In contrast, permanent technology improvements in the consumption-goods sector cause permanent increases in consumption only.

Though not directly seen in the model, TFP increases in response to both types of technology improvements. As in Beaudry and Lucke (2010) and Fernald (2014), TFP is usually computed using data for a chain-weighted measure of output, which is approximated by the Divisia index:

$$dGDP_t = \omega_t dI_t + (1-\omega_t)dC_t,$$

where GDP_t is output, d indicates the logarithmic growth rate, and ω_t is the average of the investment share in nominal output in periods t and t-1. The standard growth accounting implies

$$(26)\quad \begin{aligned} dTFP_t &\equiv dGDP_t - q_t\{u_t dK_{I,t} + (1-u_t)dK_{C,t}\} - (1-q_t)\{v_t dN_{I,t} + (1-v_t)dN_{C,t}\} \\ &= \omega_t dZ_{I,t} + (1-\omega_t)dZ_{C,t}, \end{aligned}$$

where q_t, u_t, and v_t are the weights computed by ω_t, α_I, and α_C.[10] TFP growth is a weighted average of both types of technology improvements. Summing up this equation from period 1 to t gives the level representation:

$$(27)\qquad \ln TFP_t \approx \omega_* \ln Z_{I,t} + (1-\omega_*) \ln Z_{C,t},$$

where ω_* is the sample average of the investment share. The term dropped,

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[10] As is implicit in the standard growth accounting, the log of the price dispersion term in the aggregate production function affects measured TFP. It is zero around the zero-inflation steady state up to a first-order approximation. See, for example, Galí (2008).

$\sum_{s=1}^{t}(\omega_s - \omega_*)\left(dZ_{I,s} - dZ_{C,s}\right)$, is very small because the investment share's deviation from its average is very small and indeed the maximum absolute value of the deviation for the U.S. business sector in the period 1947:1-2018:1 is 0.046.

2.2 The VAR Model

The Max Share approach currently employed in business cycle studies identifies the shock associated with the maximum forecast-error variance share in a target variable, but does not allow one to exploit the two steady-state properties explained above. Thus, this paper develops a constrained Max Share approach where the identified shock accounts for the maximum forecast-error variance share in one variable at a pre-specified horizon, subject to the constraint that it accounts for essentially none of the forecast-error variance share in another variable.

Let y_t be a m×1 vector of observables of length T. The moving average representation is given by $y_t = B(L)u_t$, where u_t is a m×1 vector of prediction errors with variance-covariance matrix $\mathrm{E}(u_t u'_t) = \Sigma$ and $B(L)$ is a matrix of lag polynomials. It is assumed that there exists a linear mapping between the prediction errors and structural shocks, $u_t = A\varepsilon_t$, where ε_t is a m×1 vector of structural shocks characterized by $E(\varepsilon_t \varepsilon'_t) = I$ and A is a m×m matrix satisfying $AA' = \Sigma$. This paper obtains A by a Cholesky decomposition of Σ and denotes it by $\tilde{A}$. The permissible impact matrix can be written as $\tilde{A}\,D$, where D is a m×m orthonormal matrix satisfying $D'D = I$.

Let γ be a column of D. $\tilde{A}\gamma$ is the impulse vector that indicates the effect of a shock on each variable. The forecast error variance share of the ith variable attributable to the shock at horizon h is,

$$\Omega_i(h) = \frac{\sum_{l=0}^{h} B_{i,l}\tilde{A}\gamma\gamma'\tilde{A}'B'_{i,l}}{\sum_{l=0}^{h} B_{i,l}\Sigma B'_{i,l}}$$

where $B_{i,l}$ is the ith row of the lag polynomial evaluated at $L = l$. The standard Max Share approach identifies the shock associated with the maximum forecast-error variance share in the variable i by solving the following maximization problem for a given value of h.

$$\max_{\gamma} \Omega_i(h)$$

$$\text{s.t.} \qquad \gamma'\gamma = 1.$$

Faust (1998) and Uhlig (2004) show that γ is given by the eigenvector associated with the maximum eigenvalue of the m×m cross-moment matrix of the impulse responses of variable i to the orthogonalized shocks, $\sum_{l=0}^{h}\left(B_{i,l}\tilde{A}\right)'\left(B_{i,l}\tilde{A}\right)$.

Instead, this paper solves the following maximization problem numerically:

$$\max_{\gamma} \Omega_i(h)$$

$$\text{s.t.} \qquad \gamma'\gamma = 1 \ \text{ and } \ \Omega_j(h) \leq \kappa.$$

The constrained Max Share approach identifies the shock that accounts for the maximum forecast-error variance share in variable i subject to the constraint that its contribution to the forecast-error variance share in variable j is no more than κ.[11] In this paper, variable i is labor productivity in investment units and variable j is the log-linear combination of labor productivity and the relative price of investment. The value of κ has to be small enough to make the constraint binding and this paper chooses κ=0.01, since it is smaller than the lower bound of the 95-percent confidence interval of $\Omega_j(h)$ computed by the standard Max Share approach (0.018). The standard Max Share approach gives the initial γ for the numerical optimization as well. The identified investment-specific technology shock $\varepsilon_{IS,t}$ is recovered using the following relationship:

$$\varepsilon_{IS,t} = \gamma'\tilde{A}^{-1}u_t.$$

This paper sets the baseline h at 32 quarters to exclude the effects of business cycles, which are typically defined as cycles in the range of 1.5 to 8 years (Christiano and Fitzgerald 2003).

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[11] This paper uses the RATS BFGS method for the numerical optimization. See Estima (2014).

This paper estimates the VAR model with seven variables ordered as follows: labor productivity in investment units, the log-linear combination of labor productivity and the relative price of investment, TFP, labor inputs, real nondurable and service consumption, the nominal investment-output ratio, and noninvestment-goods inflation. The subsets of these variables allow one to recover the responses of the relative price of investment, real output, and real investment. While the Schwartz and Hannan-Quinn criteria both chose two (from up to eight) lags, the likelihood ratio test chose seven. This paper chooses four, since it is between them and is the conventional number in estimating VAR models with quarterly data.

3. Data

The sample period is 1949:1-2018:1 and the data source is the National Income and Product Accounts (NIPA) unless noted.[12] The numerator of labor productivity is nominal business output divided by the deflator for private nonresidential fixed investment and the denominator is labor inputs measured with Fernald's (2014) cost-share weighted series that reflects the contribution of worker characteristics as well as that of raw hours.[13] The relative price of investment is measured by the ratio of the investment deflator to the deflator for total noninvestment demand, which is the difference between output and investment, since such a measure is consistent with the model.[14] In computing the linear combination of labor productivity and the relative price of investment, this paper uses the capital share estimated by Basu, Fernald, Fisher, and Kimball (2013). TFP is measured with Fernald's (2014) quarterly utilization-adjusted series. The nominal investment-output ratio is measured by the ratio of investment to business output in investment units. Labor inputs and nondurable and service consumption in the VAR model are converted to per capita terms by dividing them by the

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[12] The initial quarter is determined by the availability of the quarterly population series to construct per capita series.

[13] Investment does not include durable consumption to be consistent with the model. Fernald's (2014) data are available at his website (https://www.frbsf.org/economic-research/economists/john-fernald/).

[14] The latter deflator is computed using the Fisher ideal chain index formula (see, e.g., Whelan 2002).

civilian noninstitutionalized population aged 16 and over.[15]

Greenwood, Hercowitz, and Krusell (1997, 2000) use Gordon's (1990) annual quality-adjusted series for equipment price in measuring the investment price and Fisher (2006) interpolates Gordon's (1990) and Cummins and Violante's (2002) annual quality-adjusted series for the equipment price. In contrast, this paper uses the NIPA series in the baseline estimation. This treatment follows Justiano, Primiceri, and Tambalotti (2011) and Ben Zeev and Khan (2015) and the reason is the same as theirs. First, the coverage of Fisher's (2006) series is limited to 1955:1-2000:4.[16] Second, the Bureau of Economic Analysis (BEA) introduced quality-adjusted price indexes for computers and peripherals in 1985 and later developed estimates back to 1959, old enough to cover the period where computers were of importance. Landefeld and Grimm (2000) show that the BEA estimates for computer-price declines are in the range of other studies' estimates based on micro data. In addition, the quality adjustments are not limited to computers and peripherals and cover around 10 percent of private nonresidential fixed investment in 2015.[17] If the BEA makes quality adjustments to components with rapid quality improvements, the NIPA aggregate investment deflator should measure investment prices correctly. Indeed, Landefeld and Grimm (2000) state that the impact of quality adjustments is small in most of the adjusted components that account for 18 percent of GDP. Nevertheless, since prices are inherently measured with error, this paper assesses the robustness of results to price measurements by extending Fisher's (2006) equipment price series.

Figure 1 plots the four series: labor productivity in investment units, labor productivity

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[15] The Fisher ideal chain index formula is used for constructing the nondurable and service consumption series. The output of households and institutions serving households is subtracted since they are not included in business output. Data for population are published by the U.S. Bureau of Labor Statistics and downloaded from the Federal Reserve Bank of St. Louis's FRED.

[16] Some authors, including Schmitt-Grohé and Uribe (2011), extend Fisher's (2006) series to later periods, but only up to the pre-2010 period.

[17] See BEA's website (https://www.bea.gov/sites/default/files/papers/hedonic%20update%20Aug%202016.pdf).

raised to the power of the labor share in the investment goods sector, the log-linear combination of labor productivity and the relative price of investment, and the inverse of the relative price of investment. The second and third series are expected to follow the level of technology in the investment- and consumption-goods sectors in the long-run, as seen in equations (22) and (23). The two series move roughly together until the early 1980s. Then the consumption-goods technology appears to stop improving until the mid-1990s. In contrast, technology improvements in the investment-goods sector continued steadily and accelerated in the mid-1990s. The speedup of technology improvements in both sectors from the mid-1990s to the mid-2000s, albeit at much slower pace in the consumption-goods sector, argues in favor of the hypothesis that information technology has contributed to both IT-production and IT-use sectors as a general purpose technology (Fernald 2015). In the mid-2000s, technology improvements in the investment-goods sector decelerated and the consumption-goods technology stopped improving again. This observation is consistent with Fernald’s (2015) finding that trend productivity growth slowed several years before the Great Recession.

This paper interprets the observed divergence of the two series as indicating that technology in the investment- and consumption-goods sectors should be modelled separately. The relative-price approach would have to interpret it as indicating that the driving force of technology improvements had been sector-neutral technology until the early-1980s and switched to investment-specific technology thereafter. This paper assesses the plausibility of the two interpretations using the VAR results.

4. Results

This section shows the effects of the identified investment-specific technology shock. For comparison, this section also shows the effects of the shock identified by applying the relative-price approach to the VAR model where labor productivity is replaced with the relative price of investment.

4.1 The Effects of the Investment-Specific Technology Shock

Figure 2 shows impulse responses to the shock identified by this paper's approach. The 95-percent confidence bands are computed by a residual-based bootstrap procedure repeated 2000 times. Labor productivity increases while the response of its log-linear combination with the relative price of investment is not statistically significant at almost any horizon. The two responses are what the constrained max-share approach is expected to give and indicate that the shock reflects technology change in the investment-goods sector, but neither technology change in the consumption-goods sector nor nontechnology change. The insignificant response of the nominal investment-output ratio also indicates that the shock does not reflect nontechnology change.

The long-run responses of TFP, output, investment, and consumption are all positive and consistent with the theoretical effects of an investment-specific technology shock. TFP gradually increases to a level above the initial response and such a response suggests that the identified shock reflects the arrival of news that later materializes in actual technology change. Output, investment, consumption and labor inputs continue to increase up to the one- or two-year horizon and thus the identified shock induces positive business-cycle comovement among the macroeconomic aggregates. The impact responses of investment and labor inputs are around zero and could be explained by investment adjustment costs. As shown by Vigfusson's (2004) model simulations, since such costs lead to a limited increase in output by making investment demand inertial, an increase in labor inputs in response to technology improvements is smaller than in the case of no such costs.

Table 1 shows the share of the forecast error variances attributable to the identified investment-specific technology shock. The shock accounts for 82 percent of the forecast error variance share of labor productivity at the eight-year horizon, where the share is maximized for identification. In contrast, it accounts only for 1 percent of the share of the log-linear combination of labor productivity and the relative price of investment. These results show that, on average over the sample period in the U.S. data, the role of sector-neutral technology shocks is small. The identified shock's small role in fluctuations in the nominal investment-output ratio (6 percent) shows that this paper's approach effectively works to make the shock uncontaminated by nontechnology change.

The contribution to TFP fluctuations is 6 percent on impact and increases to 21 percent at the eight-year horizon. This means that the shock is dominated by the arrival of news, not by the unanticipated technology shock, and requires time to materialize in TFP change. The identified shock plays a large role in both business-cycle and long-run fluctuations in macroeconomic aggregates. At the two-year horizon, it accounts for 61, 28, 44, and 19 percent of the forecast error variance shares of output, investment, consumption, and labor inputs respectively and notably the contribution to output fluctuations is 19 percent even at the lower bound. The shock's contributions to the forecast error variance shares of output, investment, and consumption at the eight-year horizon are also large, at 71, 52, and 51 percent respectively.

The role of the investment-specific technology shock found by this paper is larger than what Fisher (2006) finds: his shock accounts for 14 and 34 percent of output fluctuations at the two-year horizon in the periods 1955:1-1979:2 and 1982:3-2000:4 respectively. However, his approach is to combine the long-run restriction identification with the relative-price approach, both of which this paper regards as problematic. Ben Zeev and Khan (2015) try to identify the news shock about investment-specific technology as the shock that best explains future movements in the relative price of investment and is orthogonal to innovations in TFP and the relative price of investment. Thus, they combine the max-share identification approach with the "brave" version of relative-price approach where the inverse of the relative price of investment is assumed to equal investment-specific technology at all times.[18] The role of their

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[18] With different factor shares between the two sectors or with markups, their orthogonality condition does not allow identification of the technology news shock since the relative price of investment responds endogenously

news shock in the U.S. business cycle is very large: the shock leads to significant increases in output, investment, and consumption and explains 73, 60, and 73 percent of those variables' forecast error variances at the two-year horizon. In contrast, very oddly, the news shock does not cause a significant response of TFP and explains little the forecast error variance of TFP. Given the identity between TFP and aggregate sectoral technology, this implies that they fail to identify the investment-specific technology shock.[19] The next section shows that it is very likely that they identify negative technology shocks in the consumption-goods sector as well as positive technology shocks in the investment-goods sector, both of which affect the relative price of investment in the same direction.

4.2 Comparison with the Relative-Price Approach

This subsection examines the relative-price approach by replacing labor productivity with the relative price of investment in the VAR model and identifying the shock that best explains future movements in the latter variable. The response of labor productivity is recovered from the responses of the relative price of investment and its linear combination with labor productivity. Figure 3 shows impulse responses. Strikingly, while the response of labor productivity is still positive, the response of the log-linear combination of labor productivity and the relative price of investment turns negative on average and is statistically significant around the two- to three-year horizon. The response of TFP is not statistically significant at any horizon and confirms Ben Zeev and Khan's (2015) result. Another large change from the baseline results is that the response of consumption is not statistically significant at long horizons.[20] The responses of TFP

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and immediately. Given the identity between TFP and aggregate sectoral technology shown in equation (27), it is conceptually possible to identify the technology news shock only by assuming orthogonality with TFP. However, Kurmann and Sims (2020) show that such an orthogonality condition makes results sensitive to revisions in Fernald's (2014) utilization-adjusted TFP series, which is used by Ben Zeev and Khan (2015).

[19] Ben Zeev and Khan (2015) only state that "[T]he effect on TFP is insignificant" for this result. Though Fisher (2006) does not have TFP in his VAR model, his approach might not suffer such a problem since he imposes the additional restriction that the investment-specific technology shock that lowers the relative price of investment raises labor productivity.

[20] Since Ben Zeev and Khan (2015) show impulse responses only up to the five-year horizon, it is unknown what their impulse responses look like in the long-run.

and consumption are inconsistent with the theoretical role of investment-goods technology. In addition, confidence bands for many variables are wider.

Table 2 shows the share of the forecast error variances attributable to the shock. Since the shock accounts for 57 percent of labor productivity's fluctuations at the eight-year horizon, it is very likely that it reflects technology shocks in the investment-goods sector. Nevertheless, its contribution to TFP fluctuations at the same horizon is only 6 percent. The shock's share in the forecast error variance of the log-linear combination of labor productivity and the relative price of investment is 15 percent at the eight-year horizon and larger than in the baseline results (1 percent). When compared with the baseline results on macroeconomic aggregates, the shock's share in the forecast error variance of consumption is especially smaller at 33 and 37 percent at the two- and eight-year horizons (44 and 51 percent in the baseline results).

A possible reason for these results is that the relative-price approach identifies a linear combination of the positive technology shock in the investment-goods sector and the negative technology shock in the consumption-goods sector, both leading to an increase in the inverse of the relative price of investment. The negative response of the log-linear combination of labor productivity and the relative price of investment is consistent with this interpretation. The smaller role of the shock in fluctuations in TFP and consumption is consistent with the two-sector model's prediction that the negative consumption-goods technology shock has negative effects on TFP and consumption. The confidence bands are expected to be large because the technology shock in the consumption-goods sector since the early 1980s has been small or infrequent, as strongly suggested by the observations in Section 3, and thus its effect is estimated imprecisely.

The role of the negative consumption-goods technology shock can be illustrated by substituting the responses of labor productivity and its linear combination with the relative price of investment, each of which should eventually follow the response of technology in each of the two sectors, into equation (27) and approximating the TFP response. Figure 4 compares the result with the TFP response. The two responses are not statistically different. In spite of the positive response of labor productivity noted above, the approximate TFP response is not statistically significant at any horizon, reflecting the negative response of the linear combination of labor productivity and the relative price investment and the large confidence bands for the two variables. The bottom row of Table 2 shows the forecast error variance share in the approximate TFP. It is far smaller than the contribution to labor productivity and does not exceed 5 percent at any horizon.

5. Robustness

As robustness checks, I ordered the target variable, labor productivity or the relative price of investment, last and set the truncation horizon to 60 quarters instead of 32 quarters. The results obtained by using the approach developed in this paper were quantitatively robust to the order change and qualitatively robust to the change in the truncation horizon.[21] When using the relative-price approach and setting the truncation horizon to 60 quarters, the impulse response of TFP was still statistically insignificant at all horizons, though the lower bound of the confidence band for the impulse response of consumption at long horizons became very slightly positive. Ordering the relative price of investment last made the confidence intervals so wide that all the responses became statistically insignificant. Thus, the superiority of this paper's approach was robust to these checks. The remainder of this section shows results from other robustness checks: testing Granger-causality, using an alternative measure of relative price of investment, and looking at sectoral technology series computed by Fernald's (2014, 2015) approach.

5.1 Granger-Causality Test

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[21] When the truncation horizon was changed, the impulse response of labor inputs to the identified shock was not statistically significant and the shock's shares in forecast-error variances of macroeconomic aggregates were smaller than the baseline results by more or less 10 percentage points.

Though the impulse response of the nominal investment-output ratio allows a comprehensive assessment of the irrelevance of the identified shock to nontechnology change, an additional check is possible by studying the relationship with identified nontechnology shocks. Such an approach is taken by Francis and Ramey (2005), Fisher (2006), and Ben Zeev and Khan (2015). This paper considers whether each of the following eight variables Granger-causes the identified investment-specific technology shock: Ramey and Zubairy's (2018) military news shock, Mertens and Ravn's (2013) personal income tax shock and corporate income tax shock, Mertens and Ravn's (2011) tax news shock, Romer and Romer's (2004) monetary policy shock, Gilchrist and Zakrajšek's (2012) excess bond premium, Kilian's (2008) OPEC oil supply shock, and Baker, Bloom, and Davis's (2016) U.S. economic policy uncertainty index.[22] The identified investment-specific technology shock is regressed on a constant and the current and four lagged values of each shock. Table 3 shows p-values for the null hypothesis that all the coefficients on the variables in question are jointly equal to zero. The null is not rejected for any of the cases.

5.2 Alternative Deflators for Investment and Consumption

The robustness of the results to price measurements is assessed by two experiments. First, this paper replaces the NIPA investment deflator with an alternative investment deflator reflecting information in Fisher's (2006) equipment deflator. Second, this paper measures the consumption-goods price using the NIPA nondurable and service consumption deflator, instead of the deflator for total noninvestment demand, since the former deflator is used very often in the literature.

This paper extends Fisher's (2006) equipment deflator to periods before 1955 and after 2000

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[22] This paper uses Romer and Romer's (2004) monetary policy shock series updated by Johannes Wieland, which is available in Ramey's (2016) dataset for the *Handbook of Macroeconomics*, downloadable at her website. Mertens and Ravn (2011) construct 17 series of anticipated tax shocks, each corresponding to the number of quarters that it would take until actual change occurs. This paper constructs a single series of tax news shocks by allocating the shocks to the dates when they arrived. This paper does not use the oil supply shock identified by the popular Kilian (2009) approach, since it could reflect news about oil demand, as argued by Wieland (2019).

by simply using the growth rate of the NIPA equipment series, since the five-year correlation between the log-differences of the two series is very high at around 0.8 at the beginning and end of Fisher's (2006) sample period. The investment deflator is constructed by combining the extended equipment deflator series with the NIPA deflator series for the other components of private nonresidential fixed investment.[23] Figure 5 compares the two equipment deflators and plots the three versions of the relative price of investment. Fisher's (2006) deflator rises less until the early 1980s and falls more thereafter, reflecting larger quality adjustments, and the cumulative difference reaches 110 percent. Investment deflators diverge less, reflecting the share of equipment investment in total investment (about 50 percent), and the cumulative difference is 60 percent. Using the nondurable and service consumption deflator makes an additional difference of 20 percent.

Figure 6 shows impulse responses to shocks identified by this paper's approach and the relative-price approach with the alternative investment deflator and Figure 7 shows impulse responses to shocks identified with the alternative deflators for both investment and consumption. The results are very similar to the results shown in Figures 2 and 3. The shock identified by this paper's approach causes significant increases in TFP and other macroeconomic aggregates. The shock identified by the relative price approach does not cause a significant response of TFP at any horizon, while causing a temporary negative response of the linear combination of labor productivity and the relative price of investment. The only noticeable change from before is that the response of consumption is statistically significant. Thus, most of this paper's main findings are robust to changes in the price measurements.

5.3 Comparison with Fernald's (2014, 2015) Measure of Sectoral Technology

Fernald (2014, 2015) measures sectoral technology change by exploiting the identity between

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[23] The Fisher ideal chain index formula is used for constructing the investment deflator. This deflator is used for constructing other series in the VAR model (i.e. labor productivity, the relative price of investment, and noninvestment-goods inflation).

TFP and aggregate sectoral technology shown by equation (26). By assuming that changes in relative technology equal changes in relative prices, his approach measures technology growth in the investment- and consumption-goods sectors as follows:

$$dZ_{I,t} = dTFP_t + (1 - w_t)\left(dP_{C,t} - dP_{I,t}\right) \text{ and } dZ_{C,t} = dTFP_t - w_t\left(dP_{C,t} - dP_{I,t}\right).$$

While this approach ignores the difference in the sectoral factor shares and the possible change in relative markups, it uses TFP instead of labor productivity and does not rely on the long-run properties of the two-sector model. Thus, his approach and this paper's approach can be viewed as complements, with distinct identification schemes and strengths.

Figure 8 plots the technology series computed by Fernald's (2014, 2015) approach, together with this paper's series for comparison.[24] The former series represent cumulative growth. The two technology series for each sector follow a similar trend. Though there are persistent differences in the level of the investment-goods technology series, those are due to temporary differences in growth in the mid-1970s. Indeed, correlation coefficients between the first differences of the two series for each sector are very high: 0.91 for the investment-goods sector and 0.82 for the consumption-goods sector. These results reinforce the plausibility of this paper's approach.

6. TFP and Sectoral Technology

There is a broad misunderstanding about the covariation between TFP and the relative price of investment. Schmitt-Grohé and Uribe (2011) assert that TFP and the relative price of investment share a common stochastic trend by finding a cointegrating relationship. They also assert that sector-neutral and investment-specific technology are cointegrated by regarding TFP and the relative price of investment as respectively indicating each type of technology. Based on multiple statistical tests, Benati (2014) admits the possibility of a common stochastic trend

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[24] This paper follows Fernald (2015) by using the TFP series unadjusted for utilization in measuring sectoral technology.

but argues against cointegration. In contrast, Beaudry and Lucke (2010) make the identifying assumption that the relative price of investment is affected by the investment-specific technology shock while TFP is not in the long-run. Their other identifying assumption is that TFP is not affected by the investment-specific technology shock in the short-run. Ben Zeev and Khan (2015) also use such an assumption when identifying the unanticipated investment-specific technology shock. This paper argues below that these studies miss the identity between TFP and aggregate sectoral technology shown in equation (27).

After testing the cointegrating relationship, Schmitt-Grohé and Uribe (2011) evaluate the importance of a shock to the common stochastic trend by estimating a one-sector real business cycle model where sector-neutral and investment-specific technology are embedded. Given their estimation result that the relative price of investment literally equals the investment-specific technology, the factor share should be common between the investment- and consumption-goods sectors in the two-sector representation.[25] Then, technology in their model is mapped to technology in the two-sector model as follows:

$$Z_{I,t} \equiv Z_{SN,t}^{1-\alpha} Z_{IS,t} \text{ and } Z_{C,t} \equiv Z_{SN,t}^{1-\alpha}. \tag{28}$$

The sector-neutral technology is raised to the power of the labor share since it is Harrod-neutral in their model. Their TFP measure, taken from the working paper version of Beaudry and Lucke (2010), is computed using NIPA data and satisfies the relationship with sectoral technology shown in equation (27). Substituting equation (28) into (27) gives

$$\ln TFP_t \approx (1-\alpha)\ln Z_{SN,t} + \omega_* \ln Z_{IS,t}. \tag{29}$$

Equation (29) shows two facts. First, TFP always reflects investment-specific as well as sector-neutral technology. Thus Schmitt-Grohé and Uribe's (2011) associating TFP only with

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[25] Given that Schmitt-Grohé and Uribe's (2011) estimate entails a standard error, this result is not inconsistent with the fact that the factor shares computed using the input-output table are different between the two sectors. In terms of the two-sector model, what Schmitt-Grohé and Uribe (2011) estimate is $(1-\alpha_C)/(1-\alpha_I)$ in $P_{C,t}/P_{I,t} = Z_{IS,t}^{(1-\alpha_C)/(1-\alpha_I)}$. Their estimate is unity with a standard error of 0.06, while Basu, Fernald, Fisher, and Kimball's (2013) results based on the input-output table imply that it is 0.93.

sector-neutral technology is incorrect and the identifying assumption of Beaudry and Lucke (2010) and Ben Zeev and Khan (2015) is not valid.[26] Second, since the relative price of investment intrinsically reflects the investment-specific technology, it shares a common stochastic trend with TFP by construction. Thus, an empirical investigation of the existence of such a trend, as in Schmitt-Grohé and Uribe (2011) and Benati (2014), is meaningless.

7. Conclusion

This paper proposes to identify the investment-specific technology shock as the shock that has a long-run effect on labor productivity in investment units but not on its log-linear combination with the relative price of investment. This approach allows permanent relative markup change, technology specific to the consumption-goods sector, and differences in sectoral factor shares, while the relative-price approach does not. This paper also proposes a constrained Max Share approach that allows one to exploit the two steady-state properties. The investment-specific technology shock identified with the U.S. data is an important source of economic fluctuations in both short- and long-run. It induces positive business-cycle comovement. In contrast, the relative-price approach seems to fail to identify the shock correctly, since TFP changes little. Finally, this paper highlights a broadly missed identity between TFP and aggregate sectoral technology, which causes covariation between TFP and the relative price of investment by construction.

This paper's results imply that, in estimating dynamic stochastic general equilibrium (DSGE) models, many papers, including Smets and Wouters (2007), Justiniano, Primiceri, and Tambalotti (2010, 2011), Schmitt-Grohé and Uribe (2011, 2012), and Khan and Tsoukalas (2012), might include a specification error by assuming investment-specific and sector-neutral technology. Justiniano, Primiceri, and Tambalotti (2011), Schmitt-Grohé and Uribe (2012),

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[26] Indeed, very oddly, Ben Zeev and Khan's (2015) identified shock explains a tiny portion of fluctuations in TFP and output while it explains more than half of fluctuations in the relative price of investment. Perhaps they mislabel nontechnology shocks that affect the relative price of investment as unanticipated technology shocks.

and Khan and Tsoukalas (2012) might underestimate the role of investment-specific technology in business cycles by equating it to the inverse of the relative price of investment, which might be negatively affected by technology improvements in the consumption-goods sector. Ireland and Schuh (2008) is a notable exception in that they estimate their model assuming investment- and consumption-goods technology and find that the two types of technology play different roles in business cycles. This suggests that results in the literature of DSGE model estimation should be reexamined using a different specification of technology.

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Table 1. Forecast Error Variance Decomposition: Investment-Specific Technology Shock

Horizon	0	4	8	16	32
Labor productivity (LP)	19.5 (1.2,45.5)	54.0 (22.7,71.4)	64.3 (32.7,77.2)	76.0 (44.0,83.6)	81.8 (41.9,88.7)
LP & RPI linear combination	2.0 (0.0,7.6)	2.0 (0.2,5.4)	1.5 (0.3,3.3)	1.4 (0.4,1.9)	1.0 (1.0,1.0)
Investment-output ratio	2.9 (0.0,26.5)	1.2 (0.2,25.0)	3.3 (0.7,21.9)	6.1 (1.2,23.1)	5.6 (1.5,22.1)
TFP	6.3 (0.1,29.8)	4.9 (0.4,28.8)	4.6 (0.7,26.4)	9.4 (3.2,28.2)	20.7 (8.3,34.9)
Output	9.0 (0.0,27.6)	40.4 (6.2,56.8)	61.1 (19.4,70.6)	69.8 (24.4,79.1)	71.1 (25.2,83.2)
Investment	0.1 (0.0,20.4)	9.9 (0.7,31.0)	28.0 (4.5,46.9)	43.7 (10.1,58.3)	51.9 (12.9,65.6)
Consumption	29.9 (0.2,56.0)	36.5 (1.4,59.1)	44.1 (4.7,66.0)	48.2 (6.4,70.3)	50.7 (8.1,73.5)
Labor input	1.1 (0.0,33.0)	7.0 (1.0,23.0)	19.2 (2.3,36.5)	25.4 (2.5,42.7)	26.2 (2.7,45.1)
Relative price of investment (RPI)	12.8 (0.3,38.7)	45.2 (16.9,66.9)	58.9 (27.5,77.0)	69.6 (36.6,83.6)	74.5 (37.3,88.0)
Inflation	17.2 (0.3,41.0)	30.9 (5.8,46.8)	29.8 (5.9,45.6)	28.6 (6.5,43.8)	28.6 (6.7,43.6)

Note: The unit is percent. The forecast horizon is in quarters. Numbers in parenthesis represent the 2.5th and 97.5th percentile confidence intervals generated by a residual-based bootstrap procedure repeated 2000 times.

Table 2. Forecast Error Variance Decomposition: Relative-Price Approach

Horizon	0	4	8	16	32
Labor productivity (LP)	5.4 (0.0,33.3)	31.4 (12.7,58.1)	38.1 (18.7,64.1)	46.3 (25.3,69.1)	56.5 (30.0,76.5)
LP & RPI linear combination	3.6 (0.0,14.1)	4.7 (0.3,18.5)	10.9 (0.8,28.6)	17.4 (1.2,40.0)	15.1 (1.4,43.6)
Nominal investment-output ratio	8.2 (0.0,36.0)	3.4 (0.4,31.1)	3.0 (0.9,24.8)	3.5 (1.4,24.9)	4.7 (2.3,28.3)
TFP	2.3 (0.0,17.3)	4.0 (0.2,21.9)	4.3 (0.3,24.5)	3.1 (0.7,22.6)	5.8 (0.9,33.0)
Output	7.3 (0.0,32.7)	38.1 (6.7,62.8)	55.9 (21.7,74.2)	63.7 (30.1,81.0)	66.0 (31.0,84.5)
Investment	0.8 (0.0,21.4)	6.8 (0.8,32.1)	20.6 (3.3,48.9)	32.0 (5.8,58.3)	38.0 (6.2,65.3)
Consumption	20.6 (0.1,46.2)	27.6 (0.9,54.4)	32.9 (2.1,60.8)	35.1 (3.2,65.3)	37.4 (2.9,69.2)
Labor input	1.4 (0.0,15.8)	13.7 (0.7,36.7)	28.5 (2.5,54.1)	37.5 (4.0,63.1)	40.6 (4.3,66.0)
Relative price of investment (RPI)	26.4 (2.7,46.0)	59.2 (29.2,78.1)	72.3 (47.0,86.8)	85.1 (69.2,92.7)	91.4 (82.2,95.7)
Inflation	8.5 (0.3,38.5)	28.2 (8.7,51.8)	28.6 (9.2,51.3)	29.8 (10.5,50.8)	31.7 (11.2,51.4)
Approximate TFP	1.6 (0.0,12.1)	0.8 (0.2,11.1)	2.7 (0.4,15.1)	5.1 (0.6,23.3)	3.1 (0.9,24.7)

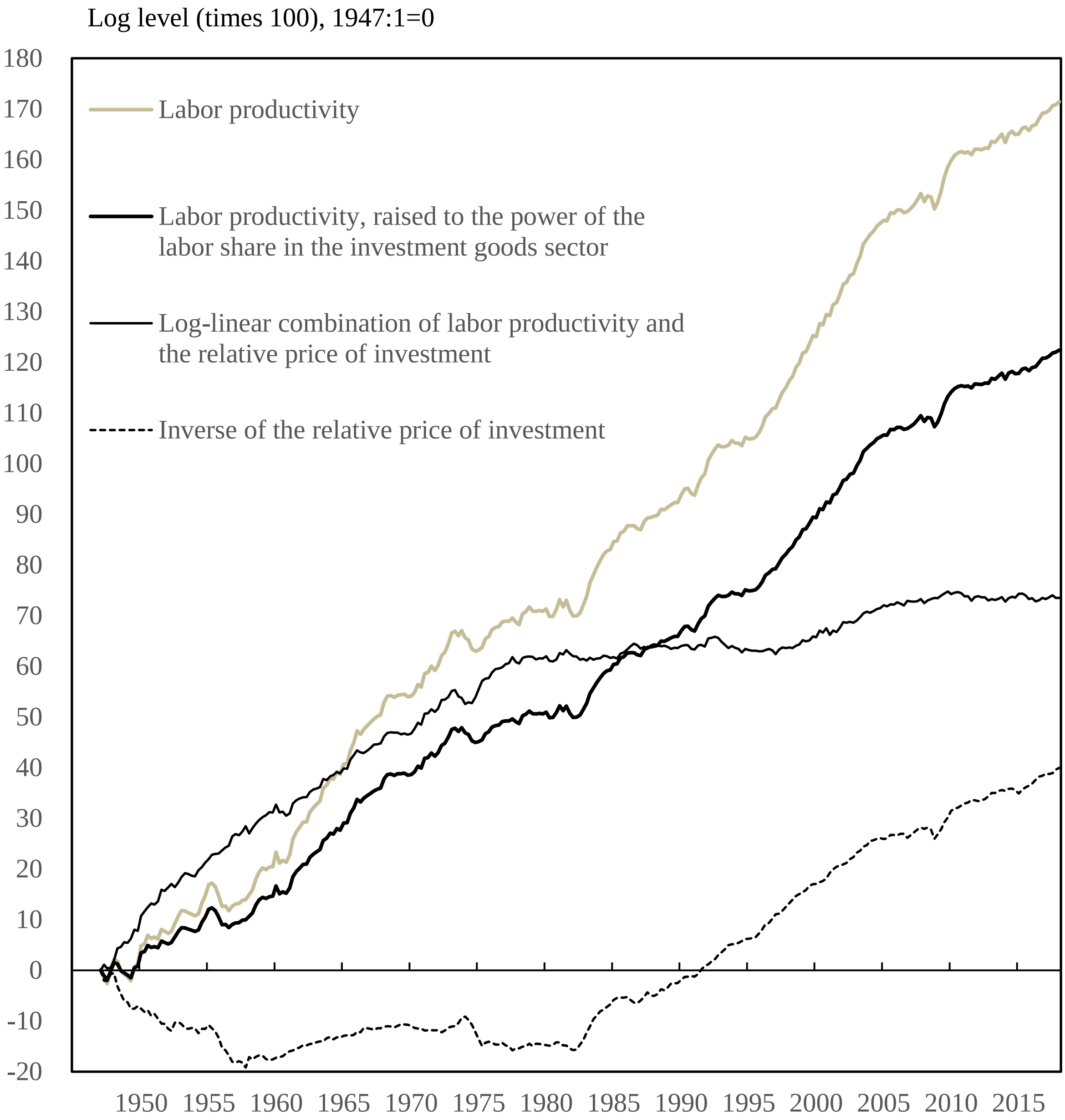
Note: The unit is percent. The forecast horizon is in quarters. Numbers in parenthesis represent the 2.5th and the 97.5th percentile confidence intervals generated by a residual-based bootstrap procedure repeated 2000 times.

Table 3. Granger Causality Test

Does the following shock Granger-cause the investment-specific technology shock?	p-value in parenthesis
Military news shock	No (0.69)
Personal income tax shock	No (0.99)
Corporate income tax shock	No (0.82)
Tax news shock	No (0.84)
Monetary policy shock	No (0.65)
Credit shock	No (0.19)
OPEC shock	No (0.20)
Uncertainty shock	No (0.76)

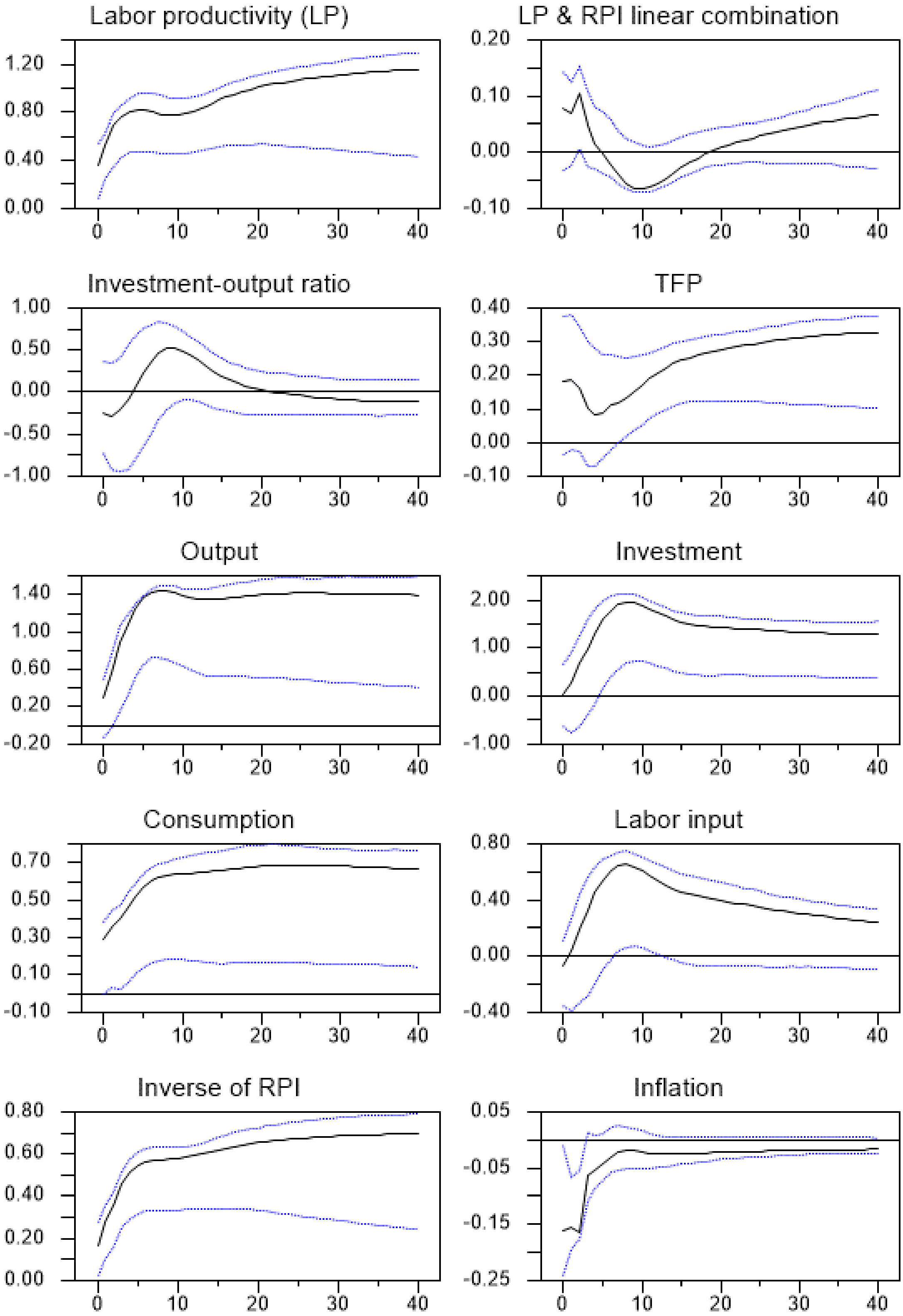
Note: The table shows results from regressing the identified investment-specific technology shock on current and four lagged values of each of the nontechnology series and testing that all the coefficients are zero. The sample period differs depending on the availability of each series; 1949:1-2015:4 for the military news shock; 1951:1-2006:4 for the personal and corporate income tax shocks; 1949:1-2006:4 for the tax news shock; 1970:2-2007:4 for the monetary policy shock; 1974:2-2016:2 for the credit shock; 1972:1-2004:3 for the OPEC shock; 1986:2-2018:1 for the uncertainty shock.

Figure 1. Labor Productivity in Investment Units and the Relative Price of Investment



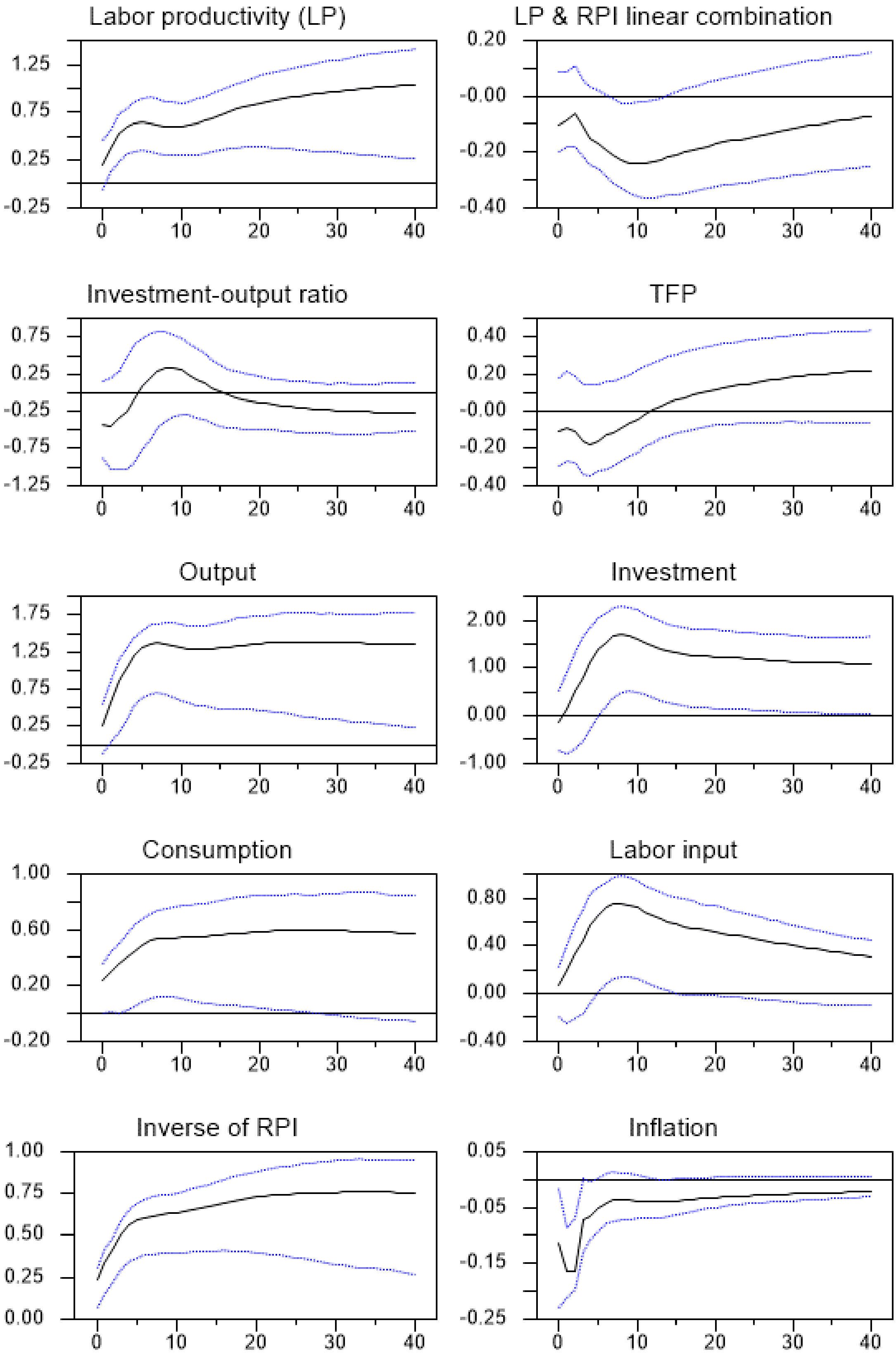
Note: Labor productivity raised to the power of the labor share in the investment-goods sector indicates the level of technology in the investment-goods sector. See equation (22). The linear combination of labor productivity and the relative price of investment is computed using the labor share in the consumption-goods sector as the coefficient. See equation (23).

Figure 2. Impulse Reponses to an Investment-Specific Technology Shock



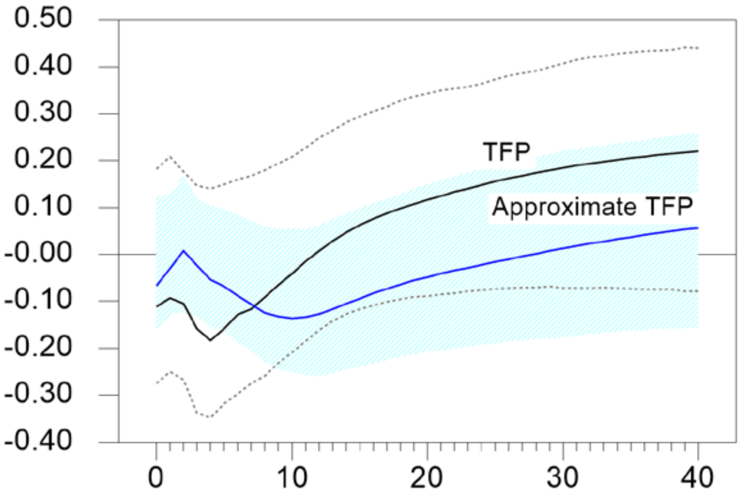
Note: The unit is percent and the horizon is in quarters. Solid lines represent impulse responses to a one percent innovation. Dashed lines represent the 2.5th and 97.5th percentile confidence intervals generated by a residual-based bootstrap procedure repeated 2000 times. The relative price of investment is abbreviated to RPI.

Figure 3. Impulse Reponses to the Shock Identified by the Relative-Price Approach



Note: The unit is percent and the horizon is in quarters. Solid lines represent impulse responses to a one percent innovation. Dashed lines represent the 2.5th and 97.5th percentile confidence intervals generated by a residual-based bootstrap procedure repeated 2000 times. The relative price of investment is abbreviated to RPI.

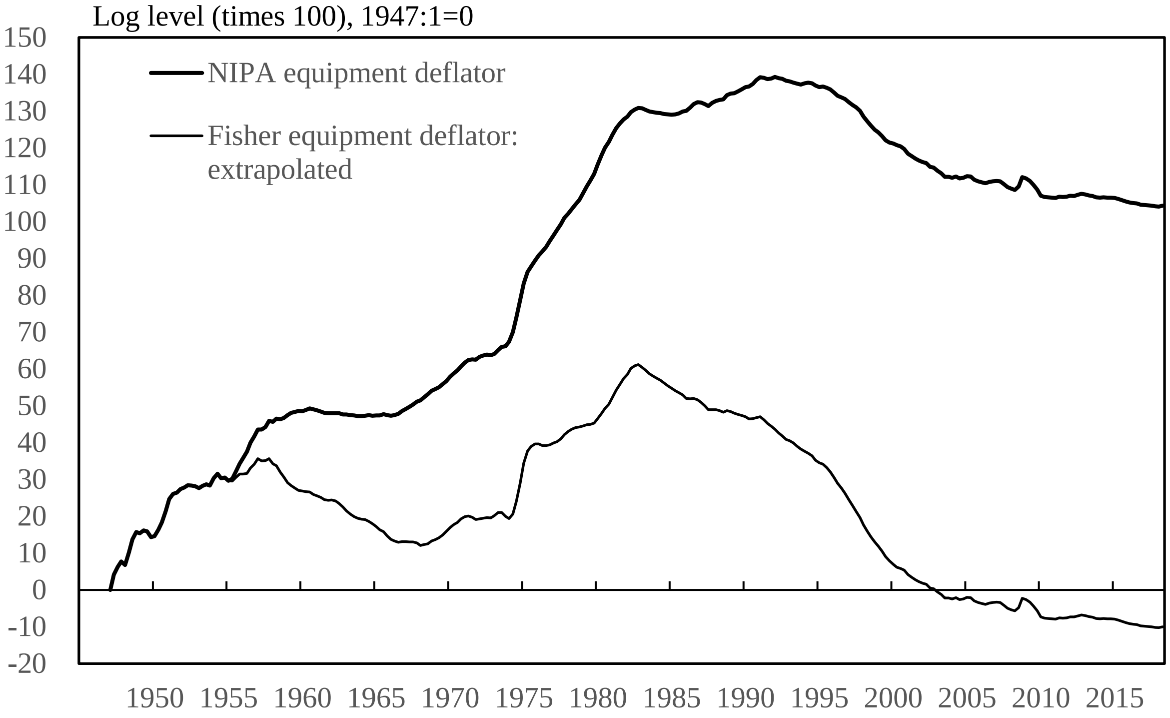
Figure 4. Impulse Response of TFP to the Shock Identified by the Relative-Price Approach



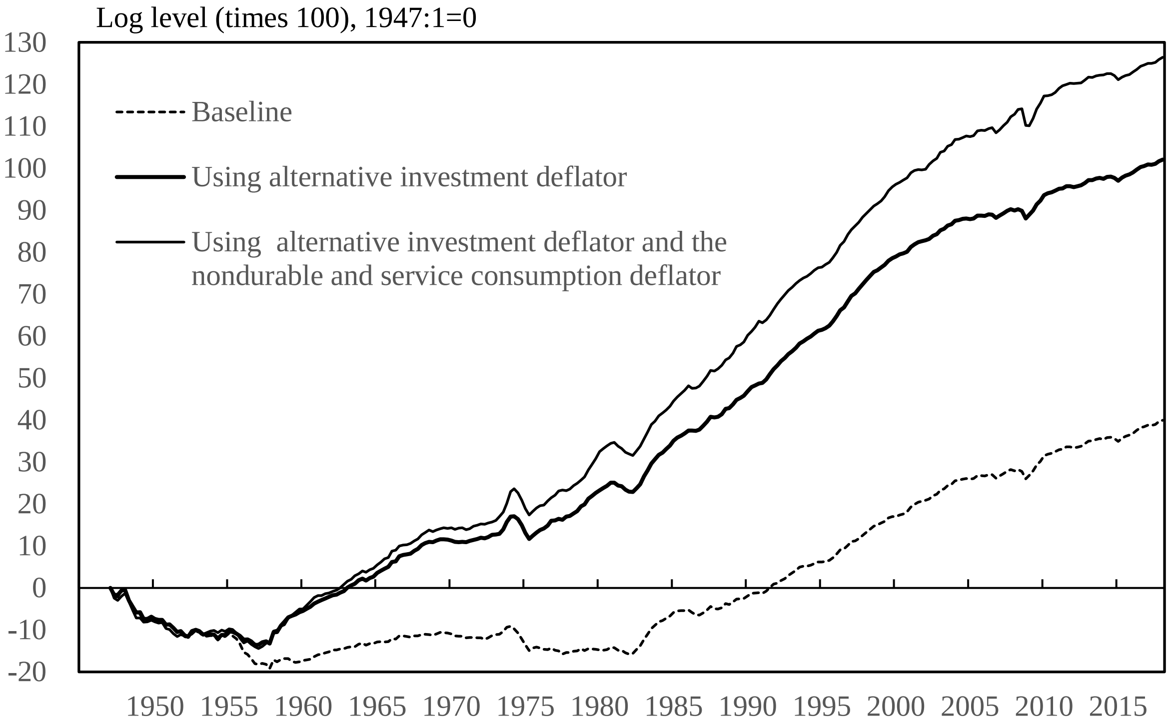
Note: The unit is percent and the horizon is in quarters. Solid lines represent impulse responses to a one percent innovation. Dashed lines and shaded band represent the 2.5th and 97.5th percentile confidence intervals generated by a residual-based bootstrap procedure repeated 2000 times. The approximate TFP is a weighted average of labor productivity and its linear combination with the relative price of investment. The weight is the share of private nonresidential fixed investment in business output.

Figure 5. Equipment Deflator and the Relative Price of Investment

Equipment deflator

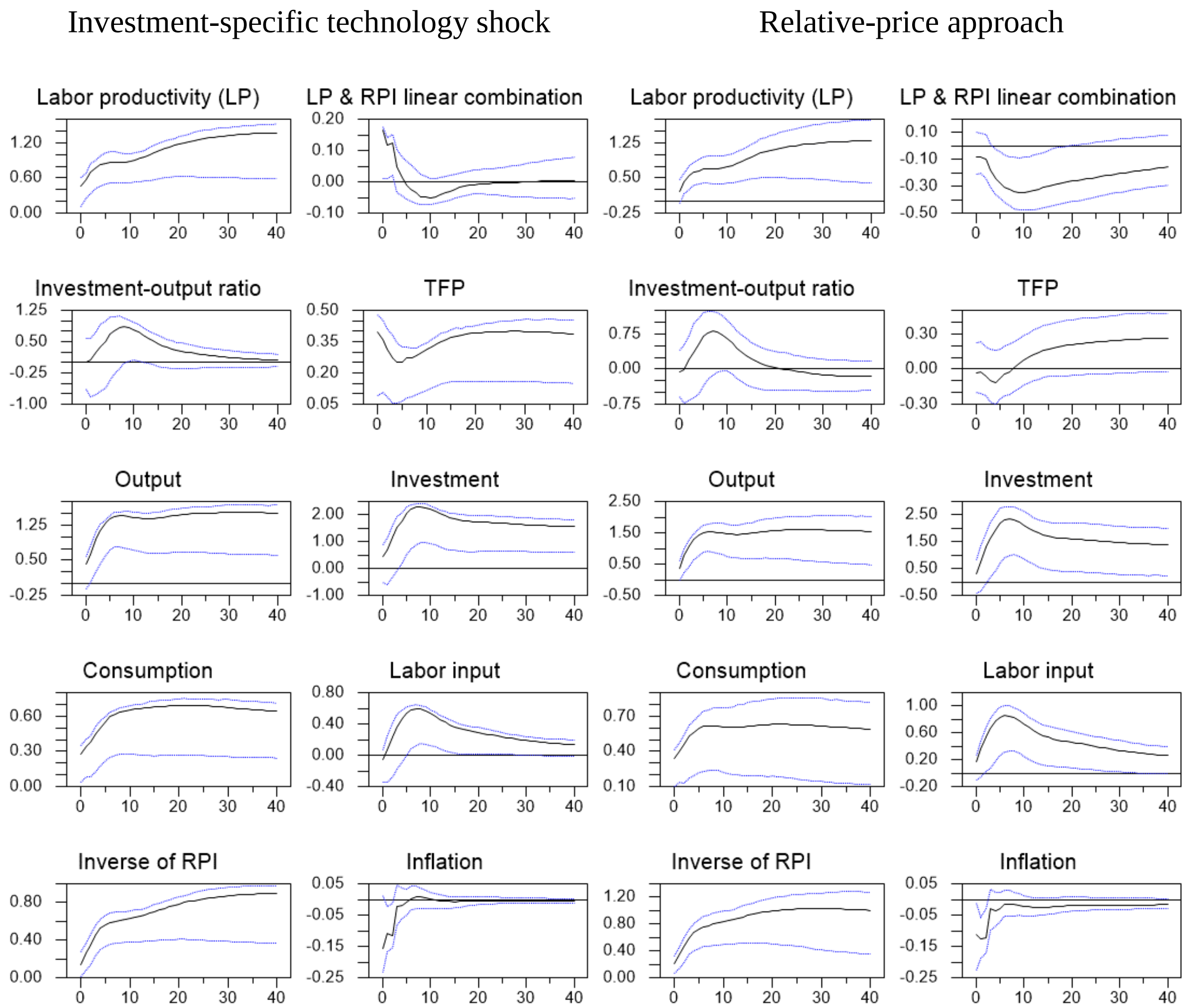


Relative price of investment



Note: The baseline series is identical to the series of relative price of investment shown in Figure 1.

Figure 6. Alternative Investment Deflator

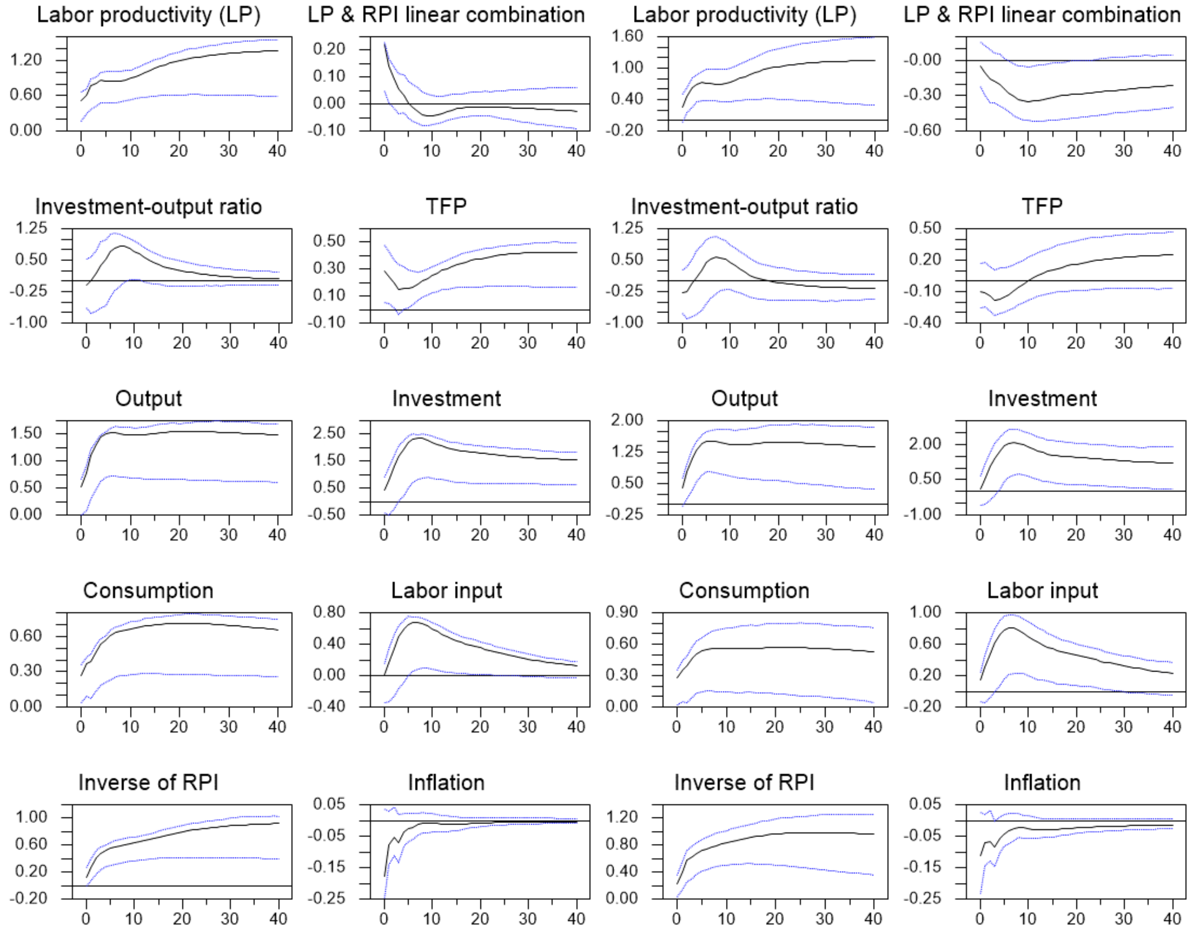

Investment-specific technology shock

Relative-price approach

Note: The unit is percent and the horizon is in quarters. Solid lines represent impulse responses to a one percent innovation. Dashed lines represent the 2.5th and 97.5th percentile confidence intervals generated by a residual-based bootstrap procedure repeated 2000 times. The relative price of investment is abbreviated to RPI.

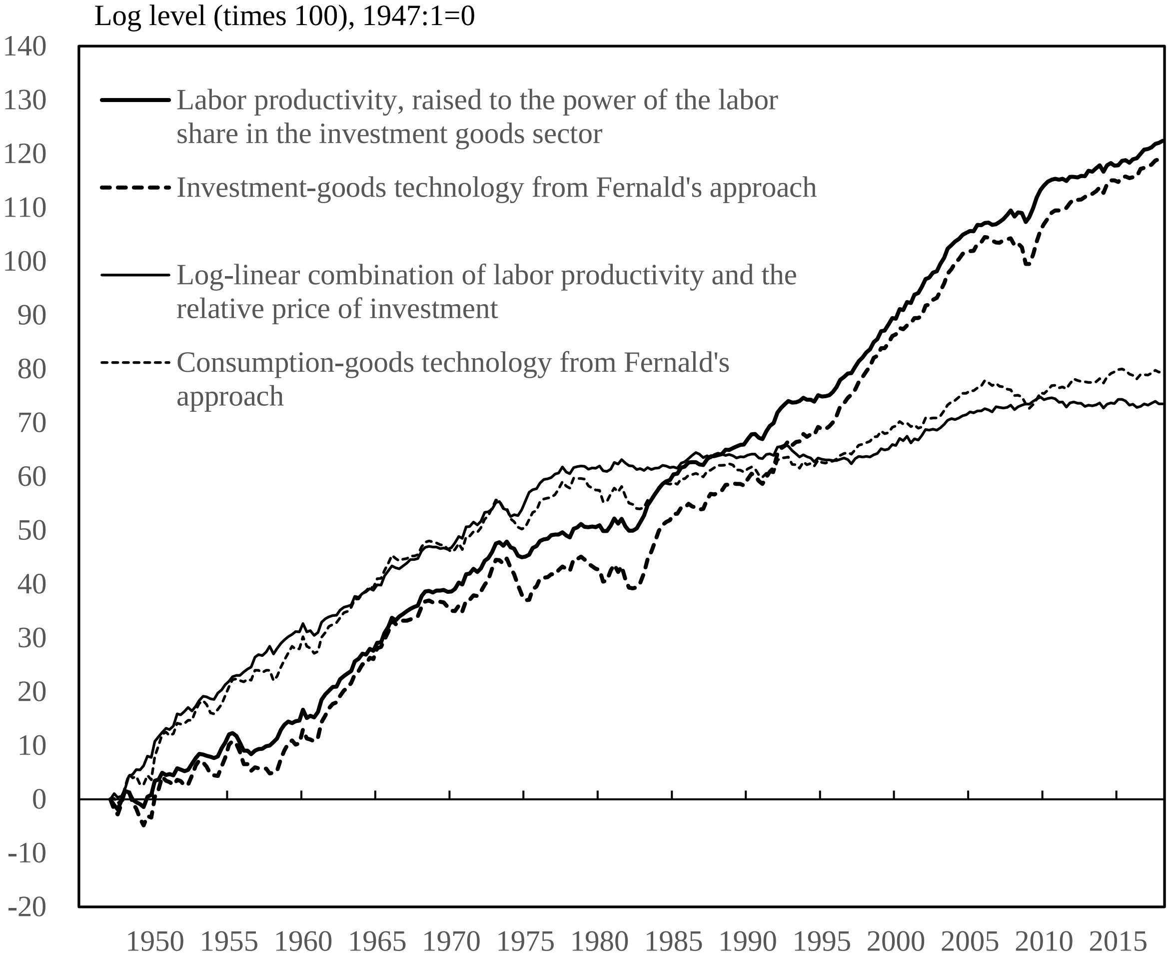
Figure 7. Alternative Deflators for Investment and Consumption

Investment-specific technology shock Relative-price approach



Note: The unit is percent and the horizon is in quarters. Solid lines represent impulse responses to a one percent innovation. Dashed lines represent the 2.5th and 97.5th percentile confidence intervals generated by a residual-based bootstrap procedure repeated 2000 times. The relative price of investment is abbreviated to RPI.

Figure 8. Comparison with Fernald’s Approach to Measuring Sectoral Technology



Note: The series computed by Fernald’s approach represent cumulative growth. The series of labor productivity and its linear combination with the relative price of investment are identical to those shown in Figure 1.