Technological Change and Reallocation*

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Abstract

This paper considers a technological change that can be utilized only by production units adapting to the new technology. A simple firm dynamics model is used to show such an innovation enhances reallocation, whereas a technological advance that is available to all production units does not. This implication is used in structural vector autoregressions to study the driving force behind cyclical movements in reallocation and the rival/nonrival nature of technology. This paper finds that one single shock explains most of the unpredictable movements in reallocation over a three- to ten-year horizon and that this shock is closely related to the investment-specific technology shock identified by long-run restrictions. The investment-specific technology shock also accounts for more than 35 percent of hours forecast errors over a two- to ten-year horizon. These findings imply that technology shocks responsible for a large portion of economic fluctuations are the main driving force behind cyclical variation in reallocation, confirming a rival or Schumpeterian nature of technological progress.

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1 Introduction

This paper seeks to answer the following questions. What types of shocks drive cyclical movements in reallocation? What do fluctuations in reallocation tell us about the nature—rival or nonrival—of technological change?

Reallocation is a pervasive feature of market economies.[1] Reallocation also accounts for a large portion of productivity growth[2] and the pace of reallocation varies considerably over time.[3] These facts have motivated many studies to investigate the role of reallocation shocks.[4]

Whether technology is rival or nonrival has also received a lot of attention in the literature (see Acemoglu, 2009). The standard Solow and neoclassical growth models assume that technology is a nonrival good: once a new technology is developed, it can be used by any producer without precluding its use by others. In contrast, the Schumpeterian growth models (e.g., Aghion and Howitt, 1992) feature the rival nature of technology so that a technological innovation can be utilized only by some producers that adapt to the new knowledge.[5]

[1]For example, Davis and Haltiwanger (1999a) document that more than one in ten jobs is either created or destroyed every year in the U.S. Baldwin et al. (1993) show that entry and exit accounts for about 40 percent of job creation and destruction over a five-year span in the U.S. and Canada manufacturing sectors between 1972 and 1982. Eisfeldt and Rampini (2006) report that the reallocation of existing capital of publicly traded firms comprises about one quarter of the U.S. total investment from 1971 to 2000.

[2]Foster et al. (2001), for example, find that over 50 percent of productivity growth in the U.S. manufacturing sector between 1977 and 1987 is attributed to reallocation; entry and exit in turn account for half of this contribution.

[3]Davis and Haltiwanger (1999a) document that the job destruction rate ranges from 2.9 percent to 10.8 percent per quarter, while the job creation rate ranges from 3.8 percent to 10.2 percent for the U.S. manufacturing sector from 1947:I to 1993:IV.

[4]To name a few, Lilien (1982), Abraham and Katz (1986), and Blanchard and Diamond (1989) are early contributions to this large literature.

[5]Hence, like these different strands of the growth literature, I broadly interpret the rival/nonrival nature of technology as including all factors affecting the ease of technology adoption rather than the intrinsic nature of technology per se.

This paper addresses the two questions above jointly by finding a strong link between technology shocks and reallocation shocks. By reallocation shocks, I mean shocks that account for the most variation in reallocation. I show that investment-specific technology shocks account for over 50 percent of all unpredictable movements in reallocation over a four- to ten-year horizon. These results hold for various reallocation measures over the period 1993-2014; i.e, establishment turnover (entry plus exit) rates, job reallocation (creation plus destruction) rates, and capital turnover rates. Hence, investment-specific technology shocks are the main driving force behind cyclical movements in reallocation.

My findings also reveal the rival nature of investment-specific technology. If new technology is nonrival and readily available, all production units can avoid becoming obsolete and aggregate productivity can grow without the need for restructuring. Technological progress entails incessant reallocation only when new knowledge is rival, thereby involving the replacement of outdated units by new ones. Hours rise gradually after an investment-specific technology shock, which explains more than 35 percent of the unpredictable variations in hours over a two- to ten-year horizon.[6] Therefore, technology shocks responsible for a large portion of aggregate fluctuations are rival and disruptive, leading to increased reallocation.

In sum, this paper finds that technological progress fostering an ongoing reallocation is a major driver of economic fluctuations. This finding confirms the importance of Schumpeterian creative destruction for reallocation and macroeconomic fluctuations.

[6] These findings are consistent with the business cycle literature documenting investment-specific technological change as a major source of business cycle fluctuations [e.g., Greenwood et al. (2000), Fisher (2006), and Justiniano et al. (2010)].

My analysis starts by constructing a simple firm dynamics model and demonstrates the different impact of various types of technological change on reallocation. The economy consists of plants and potential entrants. Plants produce aggregate output with their plant-specific productivity and can exit the market by selling off their capital. Potential entrants are those who possess new technology and they can build new plants by purchasing capital goods. There are three types of technology shocks. First, nonrival investment-neutral technology shocks enhance the productivity of *all* plants. Second, nonrival investment-specific technology shocks lower the price of capital goods traded by *all* plants. The third type are rival technology shocks, which increase the average productivity level of new technology that can be implemented by *startups only*. Note that the third type of technological progress can be either investment-neutral (e.g., new skills or organization) or investment-specific (e.g., new vintage capital).[7] A rival technology shock is distinctive in that it is not available to all production units. Also note that if this third type of technology shock is investment-specific, it will also lower the quality-adjusted price index for capital goods.

All three types of shocks in this economy encourage entry and result in an economic boom. However, only the third type increases exit as well: only new plants become more productive and the widened productivity gap between entrants and incumbents makes old plants less valuable in production. In contrast, the other two types of shocks do not encourage exit because they affect new and old plants equally.

[7] The rival/nonrival distinction is orthogonal to the investment-specific/neutral distinction. The investment-specific/neutral—capital embodied/disembodied—distinction focuses on whether a technological advance is mediated through capital formation. On the other hand, the rival/nonrival distinction focuses on whether a technological advance is mediated through unit formation. Hence, rival or Schumpeterian innovation can be called a unit-embodied technological change (Caballero and Hammour, 1996).

I then consider a vector autoregression (VAR) that combines reallocation variables with standard macroeconomic aggregates. I first identify a reallocation shock as one that accounts for most of the Forecast Error Variance (FEV) of the reallocation rate over the business cycle horizon.[8] This data-driven identification quantitatively uncovers the most important shock for reallocation but does not offer any economic interpretation. I then interpret this shock by examining its impulse responses through the lens of the theoretical model. The responses of entry/exit, job creation/destruction, and capital reallocation to this reallocation shock are similar to what is seen in the rival technology shock in my firm dynamics model.

The identified reallocation shock accounts for over 50 to 75 percent of all unpredictable fluctuations in reallocation over a three- to ten-year horizon. This shock persistently lowers the quality-adjusted price of capital goods. It is then compared to the investment-specific technology shock identified by long-run restrictions in the manner of Fisher (2006), which is the only shock to have a long-run effect on the capital goods price. I find that these two shocks are highly correlated with a correlation coefficient larger than 85 percent and their estimated impulse responses are also very similar. This finding suggests that the investment-specific technology shocks featured in the business cycle literature are the main driving force behind cyclical movements in reallocation; this Schumpeterian or disruptive technological change is a major source of business cycle fluctuations.

[8] This identification of the reallocation shock is different from previous works, which typically identify the reallocation shock as the shock orthogonal to the aggregate shock [see, for example, Blanchard and Diamond (1989), Davis and Haltiwanger (1999b), and Caballero and Hammour (2005)]. In other words, previous studies extract the shock affecting the remaining variation in reallocation after controlling for the effect of aggregate activity (expansion or contraction) on reallocation, whereas the reallocation shock in this study achieves the maximal variation in reallocation.

The positive effect of investment-specific technology shocks on reallocation in this paper is in contrast to Michelacci and Lopez-Salido (2007). They apply the same long-run restrictions[9] and find that investment-specific technology shocks decrease job reallocation and investment-neutral technology shocks increase it.[10] While their results are found on job flow data in the manufacturing sector for 1972:I–1993:IV, my finding is based on the total private sector job flow data for 1993:II–2014:II.[11] This finding of subsample instability is not new. For example, Fernald (2007) shows that there was a structural change around 1997 and that this break complicates inference about labor productivity and hours. Interestingly, I find that the investment-specific technology shocks account for less than 30 percent of the permanent change in labor productivity in 1972:I–1993:IV, whereas they account for about 80 percent in 1993:II–2014:II. Hence the primary technology shocks—investment-neutral in the early periods and investment-specific in the later periods—enhance job reallocation. These findings suggest a change in the nature of labor market or technology progress and call for further investigation.

Although Michelacci and Lopez-Salido (2007) and this paper share a common theme of technology shocks and job flows, there are important differ-

[9] Ravn and Simonelli (2007), Balleer (2012), and Canova et al. (2013) also use long-run restrictions in VAR to study the effects of technology shocks on labor market dynamics. These authors are, however, motivated by search models and analyze cyclical movements in worker flow. In contrast, this paper is interested in the effects of technological progress on restructuring production units, thereby focusing on job flow as well as establishment/capital turnover.

[10] The use of long-run restrictions in VAR for identifying technology shocks build on Gali (1999) and Fisher (2006). Gali (1999) identifies technology shocks as the only shocks that have a long-run impact on labor productivity. Fisher (2006) decomposes technology shocks into investment-specific and investment-neutral components; only the former affects the relative price of capital goods to consumption goods in the long run.

[11] The job flow data in the total private sector is available only from 1993. Michelacci and Lopez-Salido (2007) note that manufacturing employment closely tracks aggregate employment only in the period 1972:I–1993:IV.

ences. First, this paper focuses on what the reallocation dynamics reveal about the rival/nonrival nature of technological change whereas Michelacci and Lopez-Salido (2007) are interested in how investment-specific/neutral technology shocks interact differently with search frictions in the labor market. To investigate the effects of technological progress on restructuring production units in general, this paper examines establishment turnover (entry plus exit) and capital reallocation as well as job flow. Of course, search frictions and the rival/nonrival nature of technology offer two complementary, not contradictory, perspectives in interpreting the reallocation patterns in the data. Second, by constructing reallocation shocks, this paper also seeks to discover the dominant driving force behind reallocation fluctuations. I find that technology shocks not only have a positive impact on reallocation but are also the single most important force behind cyclical variations in reallocation.

The cyclicality of reallocation has been studied in many previous works. For example, Davis and Haltiwanger (1992) document contercyclical fluctuations in job reallocation and Campbell (1998) reports that the entry rate is procyclical, whereas the exit rate is countercyclical. These studies, however, are based on unconditional correlations and are not contradictory to my findings that the job reallocation and establishment turnover rates rise *conditional on* expansionary technology shocks.[12] My time-series results are also in line with the cross-section results of Samaniego (2009), who finds that industry turnover rates are positively related to the industry rates of investment-specific technological change.

[12] The countercyclicality of job reallocation in Davis and Haltiwanger (1992) comes from the fact that job destruction varies more over time than job creation. Foster et al. (2014), however, argue that this pattern is reversed during the Great Recession—job creation became more cyclically sensitive and reallocation fell. My results can be explained by these new patterns in the recent data.

My findings also provide a novel insight into the literature on capital reallocation. Using Compustat data, Eisfeldt and Rampini (2006) show that capital reallocation between firms is procyclical. As standard DSGE models with real frictions in capital reallocation only imply countercyclical or acyclical reallocation, the procyclical reallocation has been explained by procyclical capital liquidity.[13] This paper offers an alternative and complementary explanation in that the literature has considered nonrival technological progress only; however, if rival or Schumpeterian innovation that widens the gap between good and bad production units is a major source of business cycles, it could imply a procyclical reallocation even in a model without time-varying capital liquidity.

The rest of this paper is organized as follows. Section 2 uses a firm dynamics model to derive the different effects of various technological shocks. Section 3 explains my empirical approach. Section 4 presents the empirical results and Section 5 concludes.

2 Theory

This section derives different effects of various technology shocks on reallocation from a general equilibrium model of entry and exit. The model builds on a standard firm dynamics model (e.g., Hopenhayn, 1992, and more closely, Campbell, 1998) with one main difference. The standard models assume that a new entrant discovers its idiosyncratic productivity only after entry, whereas this paper follows Lee and Mukoyama (2007) and assumes a prospective entrant decides on entry after observing its productivity. The latter assumption enables the endogenous determination of the average productivity of new en-

[13] Eisfeldt and Rampini (2006) offer this explanation; Cui (2013) and Lanteri (2014) propose models endogenously generating capital illiquidity in recessions.

trants.

2.1 The Model

The economy consists of plants, potential entrants, and households. I use the term "plants" loosely in this section to mean production units at various levels of disaggregation. The entry and exit dynamics in the model will be later compared to the entry and exit of establishments, the creation and destruction of jobs, and the flow of capital across firms in the data.

A continuum of production units exists. Capital is a fixed factor at the plant level and is normalized to one. A plant cannot adjust its capital over its life cycle and all variation in aggregate capital comes from the extensive margin; that is, from the entry and exit of plants.

Each plant with a unit of capital behaves competitively and produces an aggregate good according to

$$y_t = (e^{z_t + \omega_t} n_t)^\alpha.$$

The plant's output of the aggregate good is y_t and its labor input is n_t. Labor can be adjusted freely. The plant's productivity consists of two components: z_t, which is the aggregate productivity common across all plants, and ω_t, which is the idiosyncratic productivity specific to each plant.

Aggregate and idiosyncratic productivities follow independent random walks:

$$\begin{aligned} z_{t+1} &= \mu_z + z_t + \sigma_z \epsilon^z_{t+1}, \quad \epsilon^z_{t+1} \sim \text{ i.i.d. (across time) } N(0,1), \\ \omega_{t+1} &= \omega_t + \sigma_\omega \epsilon^\omega_{t+1}, \quad \epsilon^\omega_{t+1} \sim \text{ i.i.d. (across time/plants) } N(0,1). \end{aligned} \tag{1}$$

Note that z_t represents the *nonrival* investment-neutral technology available to all plants.

Building a new plant means combining physical capital with new plant-specific technology. In each period, there is a fixed mass of potential entrants who possess new technology; the initial productivity of new technology is drawn from a normal distribution:

$$\omega_t \sim N(u_t, \sigma_e^2).$$

Once adopted at the plant level, the idiosyncratic productivity of new technology also evolves by (1). I call this idiosyncratic technology before adoption by the plant an *idea*.

u_t is the aggregate level of the technology that affects the pool of new ideas and evolves by:

$$u_{t+1} = \mu_u + u_t + \sigma_u \epsilon^u_{t+1}, \quad \epsilon^u_{t+1} \sim \text{ i.i.d. } N(0,1).$$

u_t represents the *rival* technology exclusively available to new plants only.

The potential entrant (i.e., the idea owner) makes a once-and-for-all decision about entry. If the productivity of the idea is not good enough, the idea owner decides against entry and the idea disappears. If the idea owner decides to enter the market, the owner then builds a plant by purchasing a unit of capital good. The price of capital goods is given by $e^{-\frac{\alpha}{1-\alpha}x_t}$, where x_t also follows a random walk:

$$x_{t+1} \;\; = \;\; \mu_x + x_t + \sigma_x \epsilon^x_{t+1}, \quad \epsilon^x_{t+1} \sim \text{ i.i.d. } N(0,1).$$

Once a plant is built, it acquires a disinvestment option and decides when to sell off its capital and leave the economy. If a plant decides to exit, it can recover a $e^{-\frac{\alpha}{1-\alpha}x_t}(1-\eta)$ unit of the aggregate good. Note that except for the resale loss of η, all plants—both new and incumbent—trade capital goods at the same price governed by x_t. Hence, x_t represents the *nonrival* investment-specific technology applicable to all plants.

Now consider the entry and exit decision. The idea owner enters the market if and only if the level of productivity is good enough. Similarly, the incumbent plant exits if and only if its productivity is bad enough. The optimal entry decision is therefore characterized by the productivity thresholds $\overline{\omega}_t$, above which the idea owner builds a plant and begins operation. The exit decision is in turn characterized by the productivity thresholds $\underline{\omega}_t$, below which the plant exits.

Finally, the economy is populated by a unit measure of identical households with the following utility function in consumption c_t and labor n_t:

$$v_t = \max_{c_t, n_t}(1-\beta)\left[\log c_t - \kappa n_t\right] + \beta E_t[v_{t+1}].$$

Households supply the labor and finance the investments in plants so that their wealth is held as shares in plants.

2.2 Equilibrium

I solve the social planner's problem. Let $K_t(\cdot)$ and $H_t(\cdot)$ denote measures over the plants' and ideas' productivity, respectively. Also, let $\phi(\cdot)$ denote the pdf of the standard normal distribution. The social planner's problem is then:

$$\begin{aligned} &V(K_t(\cdot), \overline{H}_t, z_t, x_t, u_t) \\ &= \max_{C_t, N_t, n_t(\cdot), \overline{\omega}_t, \underline{\omega}_t} (1-\beta)\left[\log C_t - \kappa N_t\right] + \beta E_t\left[V(K_{t+1}(\cdot), \overline{H}_{t+1}, z_{t+1}, x_{t+1}, u_{t+1})\right], \end{aligned}$$

subject to

$$\begin{aligned}
Y_t &= C_t + e^{\frac{-\alpha}{1-\alpha}x_t}\left[\int_{\overline{\omega}_t}^{\infty} H_t(\omega_t)d\omega_t - (1-\eta)\int_{-\infty}^{\underline{\omega}_t} K_t(\omega_t)d\omega_t\right], \quad (2)\\
Y_t &= \int_{-\infty}^{\infty}\left(e^{z_t+\omega_t}n_t(\omega_t)\right)^{\alpha} K_t(\omega_t)d\omega_t,\\
N_t &= \int_{-\infty}^{\infty} n_t(\omega_t)K_t(\omega_t)d\omega_t,\\
K_{t+1}(\omega_{t+1}) &= (1-\delta)\int_{\underline{\omega}_t}^{\infty}\frac{1}{\sigma_\omega}\phi\left(\frac{\omega_{t+1}-\omega_t}{\sigma_\omega}\right)K_t(\omega_t)d\omega_t \quad (3)\\
&\quad + \int_{\overline{\omega}_t}^{\infty}\frac{1}{\sigma_\omega}\phi\left(\frac{\omega_{t+1}-\omega_t}{\sigma_\omega}\right)H_t(\omega_t)d\omega_t,\\
H_t(\omega_t) &= \frac{1}{\sigma_e}\phi\left(\frac{\omega_t-u_t}{\sigma_e}\right)\times\overline{H}_t, \quad (4)
\end{aligned}$$

where $\overline{H}_t$ is a fixed mass of new idea discovery.[14] The social planner optimally chooses aggregate consumption C_t, aggregate labor N_t, labor allocation at each plant $n_t(\cdot)$, and entry and exit thresholds ($\overline{\omega}_t$ and $\underline{\omega}_t$).

Equation (3) captures the main dynamics. $H_t(\cdot)$ represents the current stock of ideas. Ideas with good enough productivity (higher than $\overline{\omega}_t$) are adopted and added to the stock of plants $K_{t+1}(\cdot)$ in the next period. This entry deploys $\int_{\overline{\omega}_t}^{\infty} H_t(\omega_t)d\omega_t$ amount of capital goods, which represents the total measure of entrants or aggregate investment in this economy. Plants with sufficiently bad productivity (lower than $\underline{\omega}_t$) exit and disappear from the next period's stock of plants. This exit releases $(1-\eta)\int_{-\infty}^{\underline{\omega}_t} K_t(\omega_t)d\omega_t$ amount of capital goods, which represents the total measure of exit or aggregate disinvestment.

Three technology processes (z_t, x_t, and u_t) have distinct effects on this economy. Nonrival investment-neutral technology z_t raises the productivity of new and old plants altogether. Nonrival investment-specific technology x_t

[14]More precisely, $\overline{H}_t$ exogenously grows in step with the stochastic trend of the economy.

affects both of the investment and disinvestment margins equally in equation (2). Rival technology u_t improves the productivity level of entrants only in equation (4). Note that u_t can be either investment-specific or neutral[15]; if it is investment-specific, it will also lower the quality-adjusted price index for capital goods.

The equilibrium conditions of the model (see Appendix A) are functional equations that require solving for the distribution of plant productivity. To deal with this infinite dimensional problem, I adopt an approach developed by Campbell (1998) of approximating the distribution functions by their values at a large but finite set of grid points and then applying a perturbation method that can handle many state variables relatively easily. I obtain the solution by using Dynare (Adjemian et al., 2011).

2.3 Effects of Technology Shocks

Figure 1 displays the impulse responses of entry and exit thresholds $\overline{\omega}$ and $\underline{\omega}$, as well as the entry and exit rates[16] to three technology shocks in the model. The pool of new ideas $\overline{H}_t$ is set to jump upon impact to a new steady state value; that is, it increases by one percent. The model period is a quarter and the plots

[15]Both investment-specific and neutral technologies can be either rival or nonrival depending on the ease of adoption. Consider, for example, investment-specific technology. Its advance can either represent: 1) A fall in the cost of producing capital goods; or 2) A quality improvement of a new vintage of capital. As Greenwood et al. (1997) show, these two interpretations are equivalent in a representative firm economy as the same representative firm replaces old capital with new. This equivalence, however, no longer holds in a heterogenous firm economy if a new vintage of capital cannot be easily deployed. A less expensive capital good affects investment and disinvestment decisions of all production units; whereas, only a production unit that possesses the necessary skills or knowledge can adopt a new vintage of capital. Hence, a capital quality improvement is rival in this case; whereas, a fall in capital good price is nonrival.

[16] $\frac{\int_{\overline{\omega}_t}^{\infty} H_t(\omega_t)d\omega_t}{\int_{-\infty}^{\infty} K_t(\omega_t)d\omega_t}$ and $\frac{\int_{-\infty}^{\underline{\omega}_t} K_t(\omega_t)d\omega_t}{\int_{-\infty}^{\infty} K_t(\omega_t)d\omega_t}$

are based on the following parameter values:[17] $\beta = 0.994$, $\kappa = 2.73$, $\alpha = 2/3$, $\delta = 0.025$, $\eta = 0.15$, $\sigma_\omega = 0.03$, $\sigma_e = 0.09$, $\mu_z = 0.0015$, and $\mu_x = \mu_u = 0.0010$. The qualitative results remain intact with different parameter values.

All three technology shocks encourage entry. Although the new idea pool increases by the same one percent, a rise in entry is bigger than one percent during the transition to the new steady state; this results in a lower entry threshold for nonrival technology shocks. The incumbent plants then compete with new plants that have lower productivity, thereby reducing the exit threshold and the exit rate. In contrast, a rival technology shock induces a rise in the productivity of new plants and the resulting competition with a better cohort of entrants pushes out old plants. Hence, the exit rate rises in this case.

The different signs of the exit responses, of course, depend on how elastically the pool of new ideas respond to the shocks; however, the different sizes of the exit responses are more robust. Note that the response of the exit rate is an order of magnitude smaller than that of the entry rate in the case of nonrival technology shocks. This comes from the fact that these shocks do not affect new and old plants differentially: a nonrival investment-neutral technology shock makes both new and old capital more productive, while a

[17] Greenwood et al. (2000) document that the average annual rate of decline in the relative real quality-adjusted price of equipment is 3.2 percent per year, adding 0.81 percent to the balanced growth rate of output. The quarterly contribution of 0.2 percent is split equally between $\mu_x = \mu_u = 0.001$ since both x_t and u_t (if u_t is investment-specific) can lower the quality-adjusted price index for capital goods. $\mu_z = 0.0015$ is set in order to imply a 1.4 percent annual growth rate of output per capita. The time discount factor β is set to match an annual interest rate of 4 percent. The disutility of labor κ is chosen so that the steady-state level of labor is 1/3. The labor income share $\alpha = 2/3$ and the capital depreciation rate 0.025 are standard. The resale loss $\eta = 0.15$ implies a 3.5 percent annual turnover rate of capital, which is in line with Eisfeldt and Rampini (2006). The idiosyncratic volatility $\sigma_\omega = 0.03$ is from Campbell (1998) and the dispersion parameter σ_e for distribution of the initial productivity draw is set large in order to represent a diverse pool. Different values of σ_e hardly affect the model results.

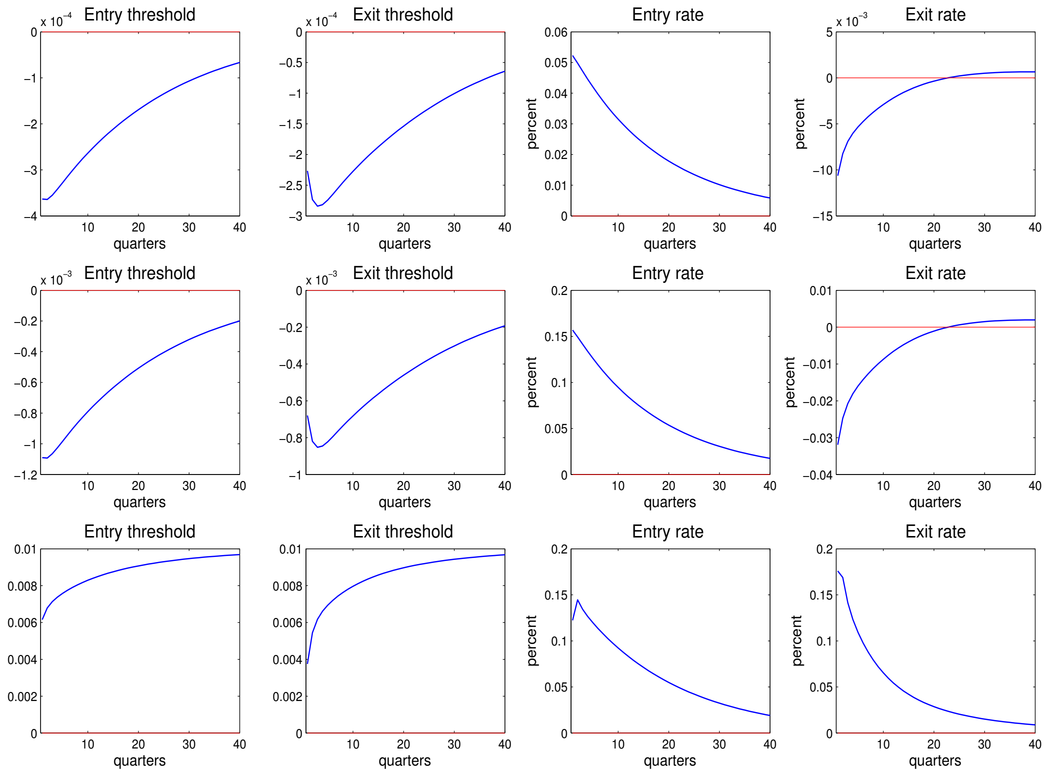

Figure 1: Impulse responses of entry and exit to a one percent increase in nonrival investment-neutral technology z_t (top panel), nonrival investment-specific technology x_t (middle panel), and rival technology u_t (bottom panel).

nonrival investment-specific technology shock lowers the value of new capital as well as the scrap value of old capital. In contrast, a rival technology shock increases both the entry and exit rates by a similar magnitude: only new units become more productive, and this widened productivity gap between entrants and incumbents makes old plants more valuable in sell-off as their capital can be deployed by more productive entrants.[18]

[18]This result is similar to Michelacci and Lopez-Salido (2007), who show in a search model that investment-neutral technological advances increase job destruction and reallocation; whereas, investment-specific technological advances that make new capital equipment

I will later show that the empirical impulse responses to the investment-specific technology shocks are characterized by a lead-lag pattern—the entry and job creation rates rise on impact, whereas the exit and job destruction rates initially fall but subsequently rise above the average for an extended amount of time. This response is predicted by a version of the model, extended to assume that more than one time period is required for exit and job destruction.[19]

3 Empirical Approach

3.1 Identification

Consider the vector moving average representation of a VAR:

$$y_t = C(L)u_t, \tag{5}$$

where y_t is a $n \times 1$ vector, $C(L) = I + C_1 L + C_2 L^2 + \ldots$ is a matrix of polynomials in the lag operator L, and u_t is a $n \times 1$ vector of one-step ahead forecasting errors with a variance-covariance matrix $E[u_t u_t'] = \Sigma$. Identification of the structural shocks amounts to finding a matrix A and a vector of mutually orthogonal shocks ϵ_t, such that $u_t = A\epsilon_t$.

The elements of y_t are $[\Delta p_t, \Delta a_t, \Delta h_t, en_t, ex_t]'$, where p_t is the log of the quality-adjusted capital good price, a_t is the log of labor productivity, h_t is

less expensive reduce job destruction. The authors assume old plants can adopt neutral technology with a small probability; hence, this technology is closer to rival technology than the nonrival neutral technology studied in my model.

[19] The responses of the existing plants to a new wave of entrants are likely to take substantial time in the real world. Liquidating and selling off existing assets takes time. In addition to physical frictions, the delay can be due to informational frictions: the incumbents might not immediately realize that the entrants have better productivity. See Appendix B for the impulse responses with a time-to-exit assumption.

the log of per capita hours worked,[20] en_t is the entry rate, ex_t is the exit rate, and $\Delta = 1 - L$.

This paper identifies the *reallocation* shock by extracting the shock that explains the maximal amount of the FEV over the business cycle horizon up to 32 quarters for the turnover rate $en_t + ex_t$.[21] First, fix $\tilde{A}$ to some arbitrary matrix satisfying $\Sigma = \tilde{A}\tilde{A}'$. Finding A is then equivalent to choosing an orthonomal matrix Q, such that $u_t = \tilde{A}Q\epsilon_t$. The k-step ahead forecast error of the turnover rate is given by:

$$en_{t+k} + ex_{t+k} - E_t(en_{t+k} + ex_{t+k}) = e_i' \left[\sum_{l=0}^{k-1} C_l \tilde{A} Q \epsilon_{t+k-l} \right],$$

where e_i is a column vector with 1 in the 4th and 5th positions and 0 elsewhere. Let q be a column vector of Q. I then solve

$$q = \arg\max_q \; e_i' \left[\sum_{k=\underline{k}}^{\overline{k}} \sum_{l=0}^{k-1} C_l \tilde{A} q q' \tilde{A} C_l' \right] e_i \quad \text{subject to } q'q = 1$$

so that $q'\tilde{A}^{-1}u_t$ is a reallocation shock.

For comparison, I also identify the investment-specific technology shock following Fisher (2006)—I impose all first-row elements except the $(1,1)$ posi-

[20] I consider the differenced hours as my benchmark case. The literature on the long-run identification of technology shocks reaches different conclusions depending on how researchers deal with the low frequency variation in hours (e.g., Gali, 1999, Christiano et al., 2004). This literature typically finds that the technology shocks are less expansionary and account for a smaller fraction of hours variation when hours enters the VAR as in differences rather than in levels. I indeed find stronger results with the level specification.

[21] This identification strategy to extract shocks that explain the majority of FEV of a target variable is developed by Uhlig (2003) and adopted in Barsky and Sims (2011), Kurmann and Otrok (2013), and Francis et al. (2014). Such identified shocks in general depend on the forecast horizon over which the FEV is maximized. The similarity between a reallocation shock and an investment-specific technology shock remains strong in my study unless I focus on a short forecast horizon of less than three years.

tion of $C(1)A$ to be equal to zero so that only the investment-specific shock has a long-run impact on the capital good price. The investment-neutral technology shock can in turn be identified by imposing that all second-row elements except the $(2, 1)$ and $(2, 2)$ positions of $C(1)A$ are equal to zero.

3.2 Data

The real price of quality-adjusted capital goods is an investment deflator for equipment and software divided by a consumption deflator for nondurables and services. This series is constructed by Liu et al. (2011).[22] They adopt the method used by Fisher (2006)[23] and extend the series to more recent periods. Labor productivity is measured by the nonfarm business series published by the Bureau of Labor Statistics (BLS).[24] Following Fisher (2006), productivity is also expressed in consumption units using the same consumption deflator that underlies the capital goods price. Per capita hours are measured with the BLS hours series for the nonfarm business sector divided by the civilian noninstitutionalized population over the age of 16.

For the entry and exit rates, I use the rates of total private sector establishment births and deaths from the BLS Business Employment Dynamics (BED) data. The BED series are quarterly and seasonally adjusted and they have been available since 1993:II. The BED defines births as those records that

[22]Their benchmark series is the quality-adjusted deflator for equipment and software, nonresidential and residential structures, and consumer durables. I instead use a version including equipment and software only because the technology embodied in equipment and software better represents the type of technology I am interested in; that is, innovation that requires restructuring the production unit. My results are slightly stronger with this deflator for equipment and software only, but the difference is small. Fisher (2006) also uses the deflator for only equipment and software as his benchmark deflator.

[23]Fisher (2006) builds on Gordon (1990) and Cummins and Violante (2002).

[24]Fernald (2012) constructs a quarterly utilization-adjusted series on TFP. I also use his measure of TFP instead of labor productivity and find very similar results.

have positive employment in the third month of a quarter and zero employment in the third month of the previous four quarters. Similarly, deaths are units that report zero employment in the third month of a quarter and do not report positive employment in the subsequent third months of the next four quarters.

The BLS BED data contain job flow rates as well. Job creation and destruction rates are defined as private sector gross job gains and job losses, respectively, as a percent of employment. They have also been available since 1993:II. These series are quarterly and seasonally adjusted.

I also consider the capital turnover rates used by Eisfeldt and Rampini (2006). They construct two capital turnover rates from the annual Compustat data—acquisitions divided by lagged total assets as well as sales of property, plant, and equipment divided by lagged total property, plant, and equipment. To obtain more observations, I follow Cui (2013) to construct the corresponding quarterly series from the quarterly Compustat data and apply a X-12-ARIMA seasonal adjustment.

4 Empirical Findings

The sample period used in this paper is 1993:II–2014:II. The baseline VAR are estimated with 4 lags of each variable and no time trend. To compute error bands, I impose a diffuse (Jeffreys) prior and display 68 percent error bands.

4.1 Baseline Estimates

Figure 2 shows the impulse responses to reallocation shocks identified by maximizing the FEV. The investment price keeps falling and the labor productivity

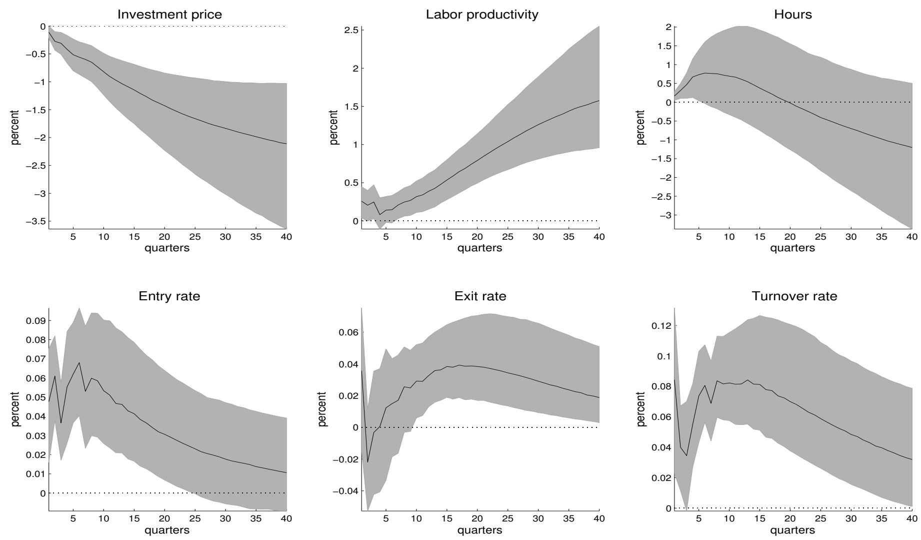

Figure 2: Impulse responses to a reallocation shock based on entry and exit data.

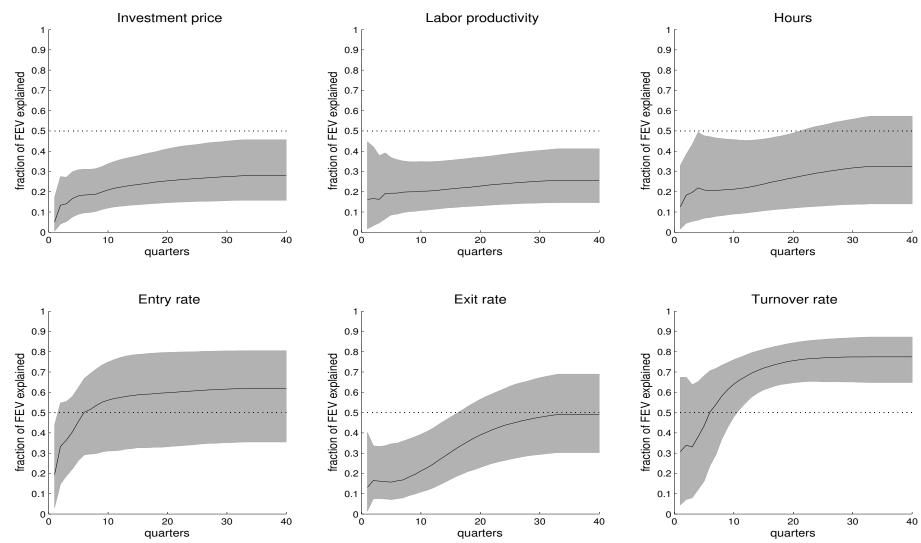

Figure 3: Fraction of forecast error variance (FEV) explained by reallocation shock based on entry and exit data.

gradually increases after an initial rise and drop. Hours respond positively and with a hump shape; the entry rate immediately rises and gradually declines, whereas the exit rate rises significantly above zero after two-and-a-half years.

Figure 3 displays the fraction of the FEV explained by the reallocation shock. It is noteworthy that the reallocation shock accounts for most medium- and longer-term variations in turnover rate. This shock by construction maximizes its contribution among possible shocks, but nothing requires that a single shock accounts for over 50 to 75 percent of all unpredictable fluctuations from one-and-a-half to ten years. Hence, the identified shock is truly a dominant driving force behind fluctuations in reallocation.

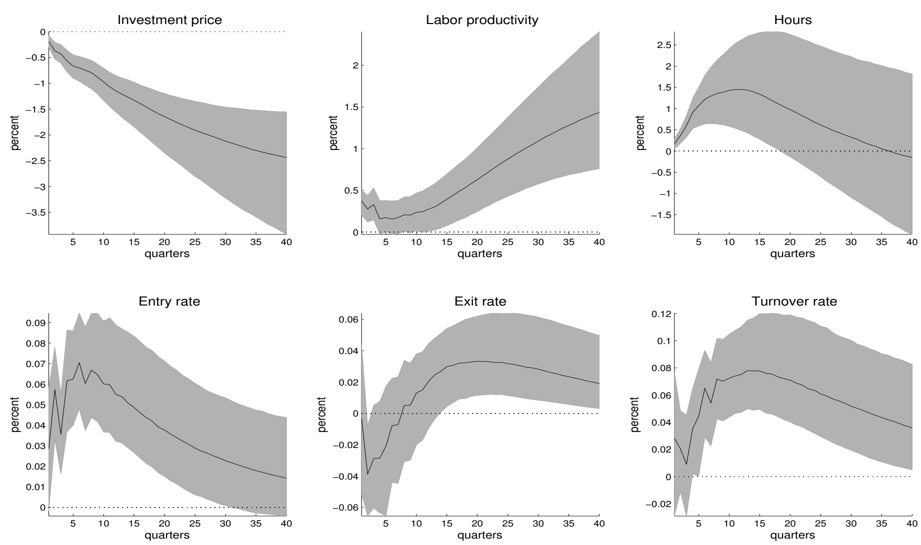

Figure 4: Impulse responses to an investment-specific technology shock based on entry and exit data.

Figure 4 displays the impulse responses to investment-specific technology shocks identified by the long-run restrictions. These results are very similar to the results for reallocation shocks.[25] The initial drop of the exit rate is

[25]The investment-specific technology shocks identified in this paper are conceptually a weighted average of rival and nonrival shocks. The strong positive effects on reallocation

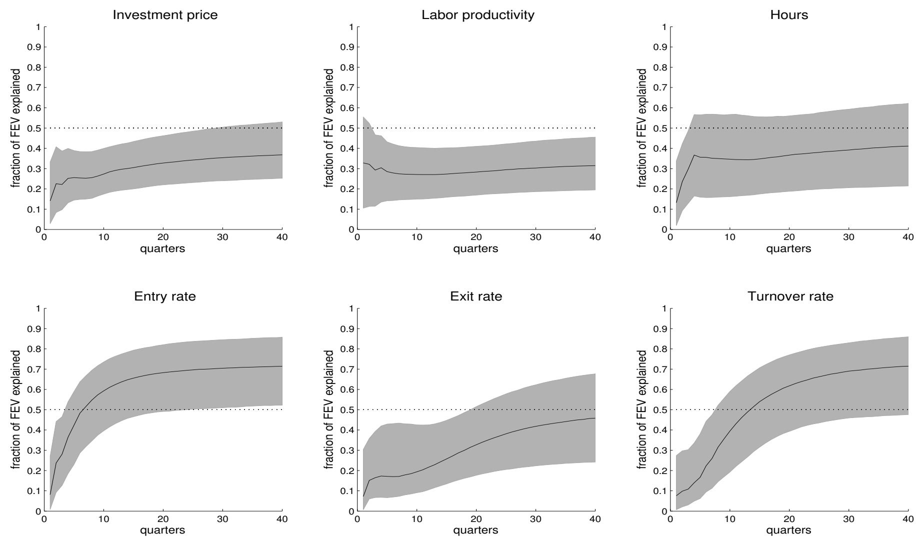

Figure 5: Fraction of forecast error variance (FEV) explained by investment-specific technology shock based on entry and exit data

more significant, but as mentioned earlier, this pattern of a lagged response of exit is consistent with a version of the model extended to include the time to exit. The fraction of the FEV explained by the investment-specific technology shock (Figure 5) is also very similar.[26] The investment-specific technology shock accounts for more than 35 percent of hours variation after one year, confirming that it is a major shock driving the business cycle fluctuations. Fisher (2006) finds that the investment-specific technology shock accounts for 9 to 22 percent of hours' FEV in the sample period of 1982:III–2000:IV. Figure

suggest that the identified shocks are mostly rival.

[26]As can be expected from the result that most variations in entry and turnover rates are accounted for by investment-specific technology shocks, the responses of reallocation rates to investment-neutral technology shocks (not shown) are weak and the error bands include zero in most periods. In addition, the hours response is no longer robust across different specifications: hours fall (rise) after a positive investment-neutral technology shock when hours enters the VAR in differences (in levels with/without time trends). I find the same results for job flow and capital reallocation data as well.

5 shows that the importance of an investment-specific technology shock is even larger in the more recent periods of 1993:II–2014:II that this paper studies.

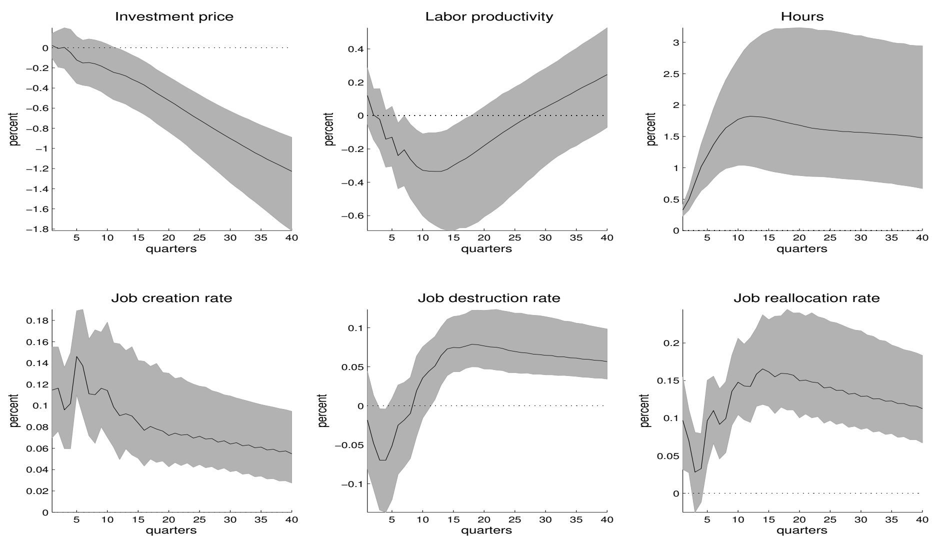

Figure 6: Impulse responses to an investment-specific technology shock based on job flow data.

I find similar results for other reallocation measures too. Figures 6 and 7 show the results when job creation and destruction rates are used in place of entry and exit rates. As the results for the reallocation shock are very similar, they are omitted from this paper. The investment-specific technology shock explains over 50 percent of the job reallocation rate's FEV for three to ten years. The impulse responses are similar to that seen in the case of entry and exit data and the only notable difference is that the labor productivity falls below zero in the medium term. Note, however, that output still rises as the hours response is larger than the productivity response.

The positive responses of job creation and reallocation rates to an investment-specific technology shock is different from the results of Michelacci and Lopez-

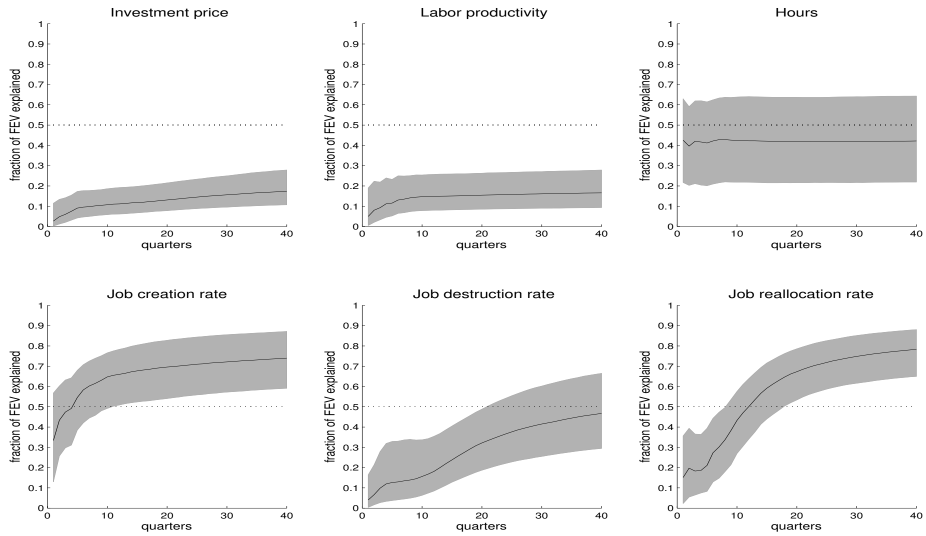

Figure 7: Fraction of forecast error variance (FEV) explained by investment-specific technology shock based on job flow data.

Salido (2007), who find that the shock leads to a fall in job destruction and reallocation rates. This difference in findings results from different data samples being used in these two studies. Michelacci and Lopez-Salido (2007) use a quarterly series of job flow in the manufacturing sector for 1972:I–1993:IV; I in fact find similar results to theirs when using this data (see Appendix C).

Interestingly, the contribution of the investment-specific technology shock to the long-run variation in labor productivity differs substantially in the two samples. The investment-specific technology shock accounts for less than 30 percent of the permanent change in labor productivity in the manufacturing sector for 1972:I–1993:IV, whereas it accounts for about 80 percent in the total private sector for 1993:II–2014:II (see Table 1). In other words, the technology shocks identified by long-run restrictions in the former sample are mostly investment-neutral, whereas they are mostly investment-specific in the latter one. Hence the dominant technology shocks enhance job reallocation in both samples,[27] which is in line with the positive relationship between reallocation and productivity growth documented in the productivity literature.[28]

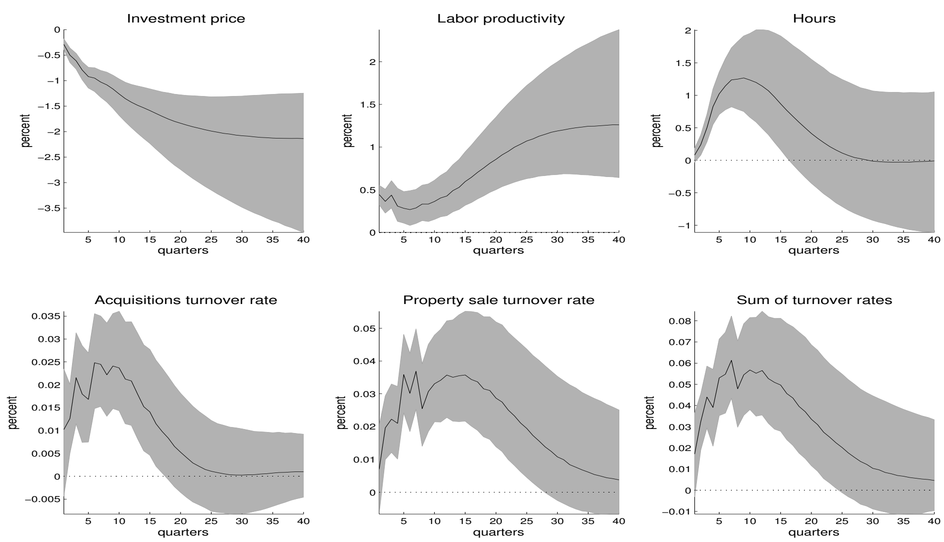

Figure 8: Impulse responses to an investment-specific technology shock based on capital reallocation data.

Figures 8 and 9 display the results when capital turnover rates are used. The elements of y_t in the VAR system (5) are $[\Delta p_t, \Delta a_t, \Delta h_t, tr_t^1, tr_t^2]'$, where tr_t^1 is acquisitions divided by lagged total assets and tr_t^2 is the sales of property, plant, and equipment divided by lagged total property, plant, and equipment.[29] Note that both turnover rates are reallocation measures,[30] whereas only the

[27] However, the hours response differs. The investment-neutral technology shock in the earlier sample is contractionary, whereas the investment-specific technology shock in the later sample is expansionary.

[28] The findings in this literature are mainly based on cross-sectional decomposition: those studies decompose the total industry-wide productivity growth over the sample period into components that reflect an improvement in individual units and the reallocation of resources across units; they find that the reallocation component is substantial. See Foster et al. (2001) and references therein.

[29] The correlation coefficient of these two series is 0.56.

[30] A reallocation shock is again identified as a shock that explains the maximum amount

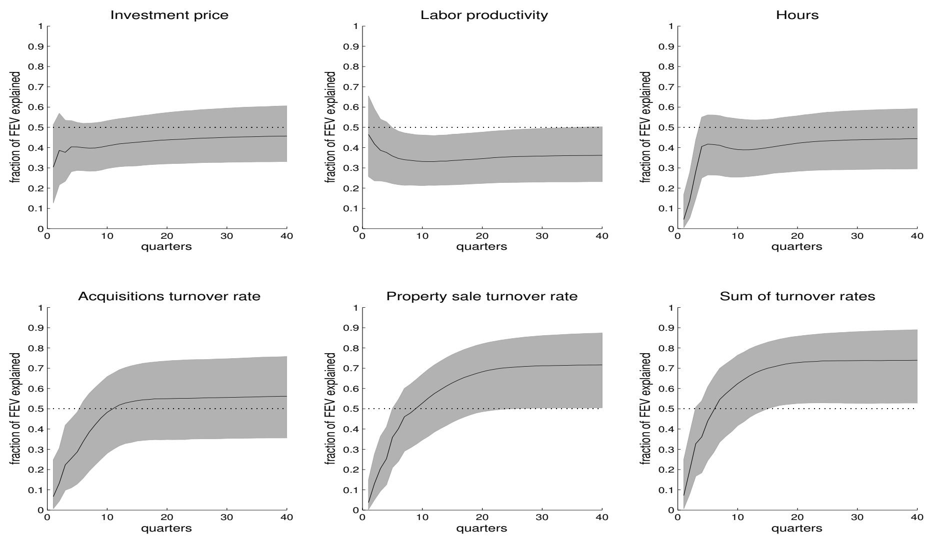

Figure 9: Fraction of forecast error variance (FEV) explained by investment-specific technology shock based on capital reallocation data.

sum of the entry and exit rates—or the sum of the job creation and destruction rates—represents reallocation in the previous cases. This explains why both rates rise together without a lead-lag pattern. The fraction of the FEV explained by the investment-specific technology shock is again large; it explains over 50 percent of the variations of the capital turnover rates after three years.

The tight link between reallocation and investment-specific technology shocks can also be seen in Table 1. The mean estimates of the correlation coefficient between two shocks are over 0.79 for all three reallocation measures. The contribution of the reallocation shock to the long-run variation in the capital goods price is also over 0.72. Note that the contribution of the investment-specific technology shock is one by definition.[31]

of the FEV of the sum of two turnover rates $tr_t^1 + tr_t^2$. The results are very similar and are therefore omitted.

[31]This contribution is computed by the ratio of the (1,1) element of $C(1)\tilde{A}qq'\tilde{A}C(1)$ to the (1,1) element of $C(1)\Sigma C(1)'$.

Data	Correlation between reallocation and investment shocks	Contribution of reallocation shock to long-run variation in capital goods price	Contribution of investment shock to long-run variation in labor productivity
entry/exit	0.795	0.725	0.802
	(0.301)	(0.272)	(0.242)
job flow	0.925	0.870	0.805
	(0.123)	(0.156)	(0.226)
capital	0.874	0.805	0.787
reallocation	(0.204)	(0.201)	(0.216)

Table 1: Entries not in parentheses are the mean estimates; the entries in parentheses are the standard deviations.

The final column represents the contribution of the investment-specific technology shock to the technological change measured by a long-run effect on labor productivity. These findings show that the investment-specific technology shock accounts for most of the permanent change in labor productivity, which is consistent with the findings of Fisher (2006) and Schmitt-Grohe and Uribe (2011). It also suggests that if a single technology shock is identified as the only shock to have a long-run effect on labor productivity, as in Gali (1999), that technology shock would also be very similar to the reallocation shock. I indeed find that this is the case; the correlation coefficient of a reallocation shock with a single technology shock is almost as high as that seen with an investment-specific technology shock.

4.2 Robustness

This subsection considers a number of potential specification issues. First, the baseline estimates focus on a 5-variable VAR system primarily because the quarterly reallocation measures of the total private sector are only available for a short sample period. However, adding two more variables considered by Fisher (2006)—nominal interest rate[32] and inflation—barely changes the strong link between the shock driving the reallocation and the investment-specific technology shock.

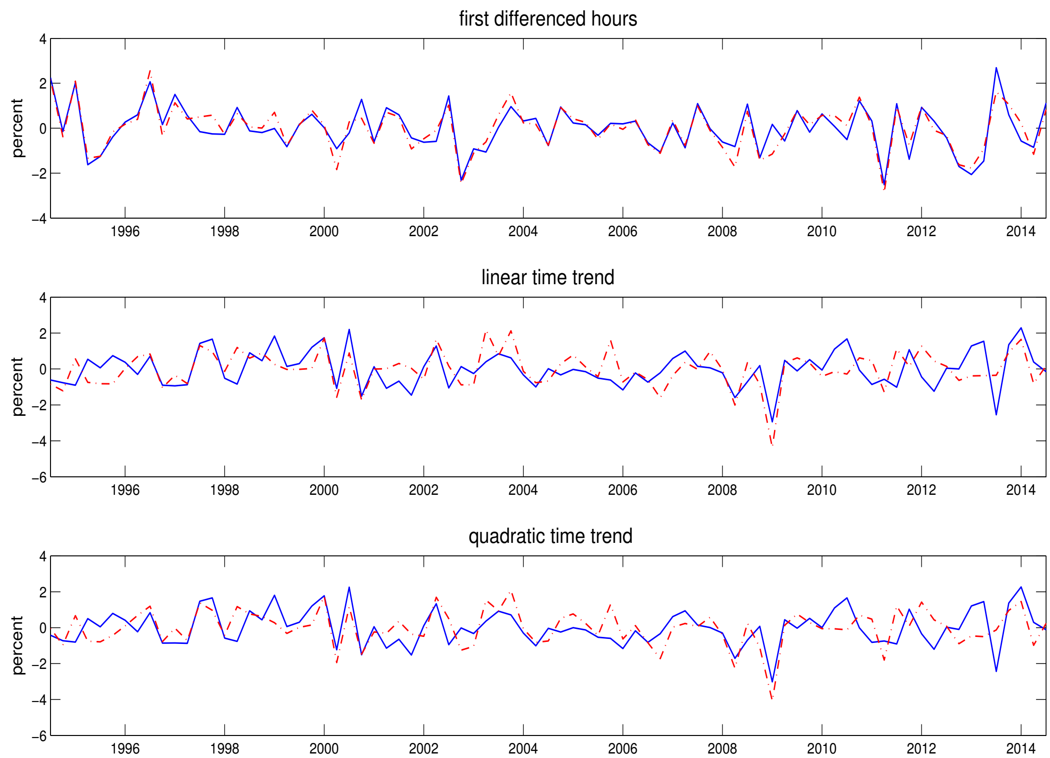

Figure 10: Comparison of the reallocation shock (solid line) and the investment-specific technology shock (dash-dot line) based on entry and exit data. Correlation coefficients are 0.92 (0.30, top panel), 0.49 (0.34, middle panel), and 0.53 (0.39, bottom panel). Numbers in parentheses are the standard deviations.

Second, the baseline specification has hours included in differences. There

[32]Because the zero lower bound becomes binding in the latter part of my sample, I also use the Wu-Xia shadow Federal Funds rate (Wu and Xia, 2014) instead of the three-month Treasury bill rate; however, the results do not change.

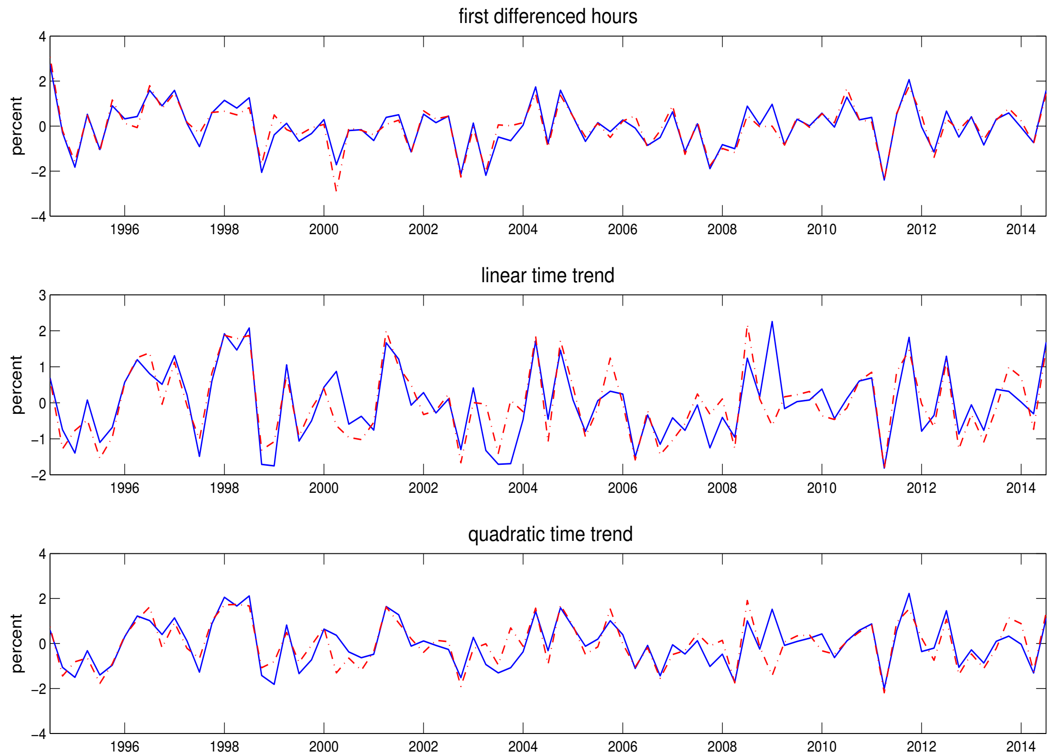

Figure 11: Comparison of the reallocation shock (solid line) and the investment-specific technology shock (dash-dot line) based on job flow data. Correlation coefficients are 0.95 (0.12, top panel), 0.82 (0.34, middle panel), and 0.82 (0.28, bottom panel). Numbers in parentheses are the standard deviations.

is a disagreement in the literature about the treatment of the low frequency component of hours [see, for example, Gali (1999), Christiano et al. (2004), and Francis and Ramey (2005)]. The literature also considers the level specification of hours with linear/quadratic detrending; these specifications lead to different conclusions about whether hours rise or fall after a positive technology shock and how important the role of the technology shocks is in explaining hours and output fluctuations. I find that hours rise after a positive investment-specific

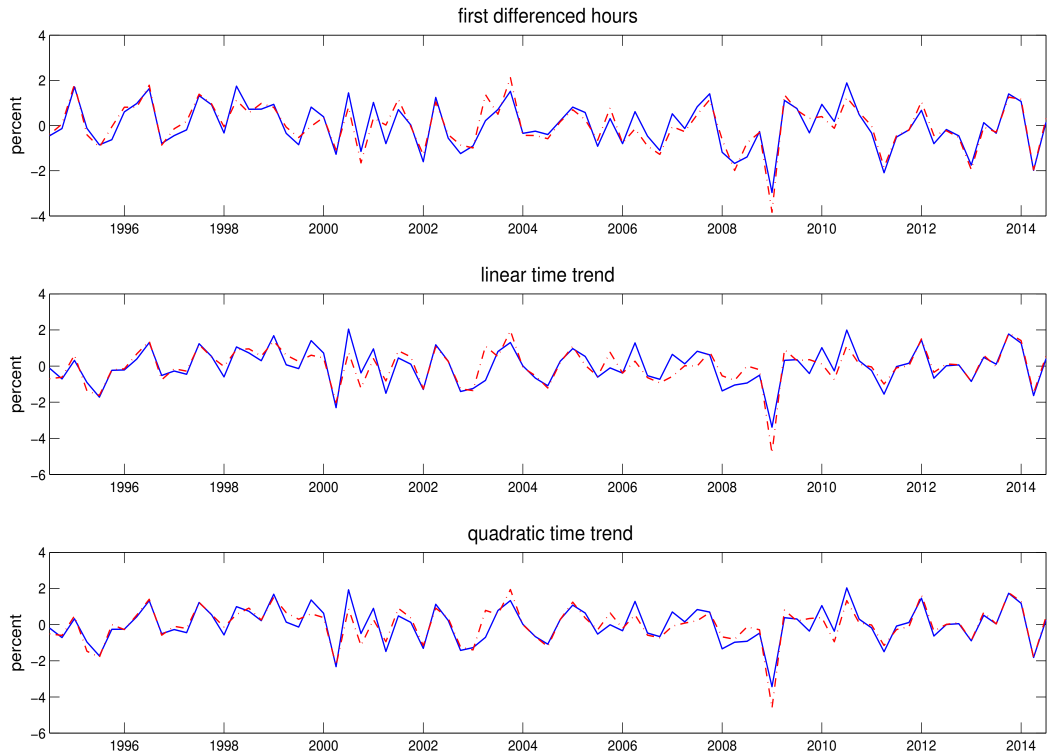

Figure 12: Comparison of the reallocation shock (solid line) and the investment-specific technology shock (dash-dot line) based on capital reallocation data. Correlation coefficients are 0.93 (0.20, top panel), 0.87 (0.20, middle panel), and 0.91 (0.29, bottom panel). Numbers in parentheses are the standard deviations.

technology shock and that the investment-specific technology shock accounts for over 30 percent of hours FEV after one year for all those specifications. Hence, the prominent contribution of the investment-specific technology shocks to cyclical fluctuations is very robust for the sample period in this paper.

More importantly, I examine the robustness of the strong correlation between the reallocation shock and the investment-specific technology shock. I find the correlation remains strong except for the entry and exit data; however, even in this case, the impulse responses to the two shocks are broadly similar. To illustrate the dependence on different specifications, Figures 10, 11, and 12 extract the time series of the reallocation and investment-specific technology shocks for the mean (OLS) estimates of the VAR parameters and plot them together.[33] I do not show the results for the level specification of hours without the time trend because the extracted shocks are almost identical with a correlation coefficient over 0.95. Although the correlation coefficients are substantially smaller for the linear/quadratic trending in the case of the entry and exit data, the two identified shocks broadly move together even in this case. For all other cases, the two shocks very closely mirror each other and represent a similar innovation to the economy.

5 Concluding Remarks

This paper studies two related questions: what drives cyclical movements in reallocation and is the technological change rival or nonrival? By showing the close link between the main shock affecting reallocation and the investment-specific technology shock, I address these questions jointly. The investment-specific technology shock is the dominant driving force behind reallocation; it is the main technological progress accounting for a large portion of aggregate fluctuations and is rival and disruptive.

My findings are subject to some caveats. Because of the data availability, this study covers a relatively short sample period, which includes only two

[33] I find that technology shocks account for a larger fraction of hours variations when the level specifications of hours with time trends are considered. This is consistent with the findings of the aforementioned papers. The contribution to reallocation variations, however, becomes smaller than the benchmark case of differenced hours, as can be seen in the lower correlation coefficient.

recessions. It is hard to judge at this time whether the difference between my findings and previous studies are due to a structural change in the 1990s or factors unique to the Great Recession.

In addition, my results rely on the premise that the long-run restriction identifies the exogenous technology shocks. A simple demand-side story cannot explain my results because increased demand would lead to a higher price of capital goods. However, if a higher demand encourages innovation in the capital goods-producing sector, resulting in lowering the quality-adjusted price of capital (in a way similar to Comin and Gertler, 2006), what I identify as a disruptive innovation could be the confounding effects of various economic shocks. Investigating the robustness of my findings to an endogenous technological change would be important and interesting and I hope to pursue this matter in future research.

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Appendix A First-order Conditions of the Social Planner's Problem

The social planner's problem in Section 2.2 can be transformed in the following ways. First, note that the labor allocation decision is atemporal so it can be solved separately:

$$\max_{n_t(\cdot)} Y_t = \int_{-\infty}^{\infty} (e^{z_t+\omega_t} n_t(\omega_t))^\alpha K_t(\omega_t) d\omega_t \quad \text{subject to} \quad N_t = \int_{-\infty}^{\infty} n_t(\omega_t) K_t(\omega_t) d\omega_t.$$

The solution is

$$n_t(\omega_t) = \frac{e^{\frac{\alpha}{1-\alpha}\omega_t}}{\widehat{K}_t} N_t, \; Y_t = \widehat{K}_t^{1-\alpha}(e^{z_t} N_t)^\alpha, \quad \text{where} \quad \widehat{K}_t = \int_{-\infty}^{\infty} e^{\frac{\alpha}{1-\alpha}\omega_t} K_t(\omega_t) d\omega_t.$$

$\widehat{K}_t$ is the productivity-weighted capital stock. Second, by replacing $H_t(\omega_t)$ with $\frac{1}{\sigma_e}\phi\left(\frac{\omega_t - u_t}{\sigma_e}\right) \times \overline{H}_t$ and integrating ω_t out, the social planner's problem can be rewritten as:

$$\begin{aligned} & V(K_t(\cdot), \overline{H}_t, z_t, x_t, u_t) \\ & \quad = \max_{C_t, N_t, \overline{\omega}_{t'}, \underline{\omega}_{t'}} (1-\beta)\left[\log C_t - \kappa N_t\right] + \beta E_t \left[V(K_{t+1}(\cdot), \overline{H}_{t+1}, z_{t+1}, x_{t+1}, u_{t+1})\right], \end{aligned}$$

subject to

$$
\begin{aligned}
\widehat{K}_t^{1-\alpha}(e^{z_t}N_t)^{\alpha} &= C_t + e^{\frac{-\alpha}{1-\alpha}x_t}\left[\left[1-\Phi\left(\frac{\overline{\omega}_t - u_t}{\sigma_e}\right)\right]\overline{H}_t - (1-\eta)\int_{-\infty}^{\underline{\omega}_t} K_t(\omega_t)d\omega_t\right], \\
\widehat{K}_t &= \int_{-\infty}^{\infty} e^{\frac{\alpha}{1-\alpha}\omega_t} K_t(\omega_t)d\omega_t, \\
K_{t+1}(\omega_{t+1}) &= (1-\delta)\int_{\underline{\omega}_t}^{\infty} \frac{1}{\sigma_\omega}\phi\left(\frac{\omega_{t+1}-\omega_t}{\sigma_\omega}\right)K_t(\omega_t)d\omega_t \\
&\quad + \frac{1}{\sqrt{\sigma_\omega^2+\sigma_e^2}}\phi\left(\frac{\omega_{t+1}-u_t}{\sqrt{\sigma_\omega^2+\sigma_e^2}}\right)\left[1-\Phi\left(\frac{\overline{\omega}_t - \frac{\sigma_e^2\omega_{t+1}+\sigma_\omega^2 u_t}{\sigma_\omega^2+\sigma_e^2}}{\sigma_\omega\sigma_e/\sqrt{\sigma_\omega^2+\sigma_e^2}}\right)\right]\overline{H}_t,
\end{aligned}
$$

where $\Phi(\cdot)$ denote the cdf of the standard normal distribution.

The economy grows because of technological progress. To solve the social planner's problem, the problem must be transformed into a stationary one. Expressing idiosyncratic productivity as deviation from idea-embodied productivity ($\omega_t^\star = \omega_t - u_{t-1}$) and dividing all variables except labor and entry/exit thresholds by the corresponding stochastic growth rates ($C_t^\star = C_t/e^{z_t+x_t+u_{t-1}}, K_t^\star(\omega_t^\star) = K_t(\omega_t^\star + u_{t-1})/e^{z_t+\frac{1}{1-\alpha}x_t+u_{t-1}}, \dots$) accomplishes this transformation. The resulting stationary problem is:

$$
\begin{aligned}
&V^\star(K_t^\star(\cdot), \Delta u_t) \\
&= \max_{C_t^\star, I_t^\star, N_t, \overline{\omega}_t^\star, \underline{\omega}_t^\star} (1-\beta)\left[\log C_t^\star - \kappa N_t\right] + \beta E_t\left[V^\star(K_{t+1}^\star(\cdot), \Delta u_{t+1})\right],
\end{aligned}
$$

subject to

$$
(\widehat{K}_t^\star)^{1-\alpha}N_t^\alpha = C_t^\star + \left[1-\Phi\left(\frac{\overline{\omega}_t^\star - \Delta u_t}{\sigma_e}\right)\right]\overline{H}^\star
$$

$$
\begin{aligned}
& & -(1-\eta)\int_{-\infty}^{\underline{\omega}_t^\star} K_t^\star(\omega_t^\star)d\omega_t^\star, \\
\widehat{K}_t^\star &=& \int_{-\infty}^{\infty} e^{\frac{\alpha}{1-\alpha}\omega_t^\star} K_t^\star(\omega_t^\star)d\omega_t^\star, \\
e^{\Delta z_{t+1}+\frac{1}{1-\alpha}\Delta x_{t+1}+\Delta u_t} K_{t+1}^\star(\omega_{t+1}^\star) &=& (1-\delta)\int_{\underline{\omega}_t^\star}^{\infty} \frac{1}{\sigma_\omega}\phi\left(\frac{\omega_{t+1}^\star-\omega_t^\star+\Delta u_t}{\sigma_\omega}\right) K_t^\star(\omega_t^\star)d\omega_t^\star \\
& & +\frac{1}{\sqrt{\sigma_\omega^2+\sigma_e^2}}\phi\left(\frac{\omega_{t+1}^\star}{\sqrt{\sigma_\omega^2+\sigma_e^2}}\right) \\
& & \times\left[1-\Phi\left(\frac{\overline{\omega}_t^\star-\Delta u_t-\frac{\sigma_e^2}{\sigma_\omega^2+\sigma_e^2}\omega_{t+1}^\star}{\sigma_\omega\sigma_e/\sqrt{\sigma_\omega^2+\sigma_e^2}}\right)\right]\overline{H}^\star,
\end{aligned}
$$

where $\overline{H}^\star$ is a constant number.

The first-order conditions are as follows:

- Optimal labor:

$$
\kappa = \frac{1}{C_t^\star}\times\alpha\left(\frac{\widehat{K}_t^\star}{N_t}\right)^{1-\alpha}.
$$

  The marginal disutility of labor equals the product of the marginal utility of consumption and the marginal product of labor.

- Plant asset pricing:

$$
\begin{aligned}
\mathcal{Q}_t(\omega_{t+1}^\star) &=& E_t\Bigg[\beta e^{-(\Delta z_{t+1}+\Delta u_t+\frac{1}{1-\alpha}\Delta x_{t+1})}\left(\frac{C_{t+1}^\star}{C_t^\star}\right)^{-1} \\
& & \times\Bigg((1-\alpha)\left(\frac{\widehat{K}_{t+1}^\star}{N_{t+1}}\right)^{-\alpha} e^{\frac{\alpha}{1-\alpha}\omega_{t+1}^\star}+I(\omega_{t+1}^\star\le\underline{\omega}_{t+1}^\star)(1-\eta) \\
& & +I(\omega_{t+1}^\star>\underline{\omega}_{t+1}^\star)(1-\delta) \\
& & \times\int_{-\infty}^{\infty}\frac{1}{\sigma_\omega}\phi\left(\frac{\omega_{t+2}^\star-\omega_{t+1}^\star+\Delta u_{t+1}}{\sigma_\omega}\right)\mathcal{Q}_{t+1}(\omega_{t+2}^\star)d\omega_{t+2}^\star\Bigg)\Bigg].
\end{aligned}
$$

The price of a plant with the idiosyncratic productivity $\omega^{\star}_{t+1}$ is the expected discounted value of the following terms: marginal product of plant with $\omega^{\star}_{t+1}$, the resale value of capital if the plant exits, and the transition probability from $\omega^{\star}_{t+1}$ to $\omega^{\star}_{t+2}$ multiplied by the price of a plant with $\omega^{\star}_{t+2}$ if the plant does not exit.

- Optimal entry:

$$
\begin{aligned}
\frac{1}{\sigma_e}\phi\left(\frac{\overline{\omega}^{\star}_t - \Delta u_t}{\sigma_e}\right) \quad = \quad & \int_{-\infty}^{\infty} \frac{1}{\sqrt{\sigma_\omega^2+\sigma_e^2}}\phi\left(\frac{\omega^{\star}_{t+1}}{\sqrt{\sigma_\omega^2+\sigma_e^2}}\right) \\
& \times \frac{1}{\sigma_\omega\sigma_e/\sqrt{\sigma_\omega^2+\sigma_e^2}}\phi\left(\frac{\overline{\omega}^{\star}_t - \Delta u_t - \frac{\sigma_e^2}{\sigma_\omega^2+\sigma_e^2}\omega^{\star}_{t+1}}{\sigma_\omega\sigma_e/\sqrt{\sigma_\omega^2+\sigma_e^2}}\right) \\
& \times \mathcal{Q}_t(\omega^{\star}_{t+1})d\omega^{\star}_{t+1}.
\end{aligned}
$$

The marginal benefit of increasing the entry threshold $\overline{\omega}^{\star}_t$ is saving the purchase cost of capital. The marginal cost is a drop in the transition probability from initial draw to $\omega^{\star}_{t+1}$ while experiencing entry, multiplied by the price of a plant with $\omega^{\star}_{t+1}$.

- Optimal exit:

$$
1-\eta \quad = \quad (1-\delta)\int_{-\infty}^{\infty} \frac{1}{\sigma_\omega}\phi\left(\frac{\omega^{\star}_{t+1} - \underline{\omega}^{\star}_t + \Delta u_t}{\sigma_\omega}\right)\mathcal{Q}_t(\omega^{\star}_{t+1})d\omega^{\star}_{t+1}.
$$

The marginal benefit of increasing the exit threshold $\underline{\omega}^{\star}_t$ is earning the resale value of capital. The marginal cost is losing a change in the transition probability from $\omega^{\star}_t$ to $\omega^{\star}_{t+1}$ multiplied by the price of a plant with $\omega^{\star}_{t+1}$.

Appendix B Time to Exit

Figure 13 shows the results when four quarters of time to exit is assumed. The exit rate initially declines in all three cases: the exit does not respond immediately by the time-to-exit assumption but the entry and the total measure of plants rise so that the exit *rate* falls. The exit response appears after the fourth quarter, displaying a lead-lag pattern between entry and exit rates.

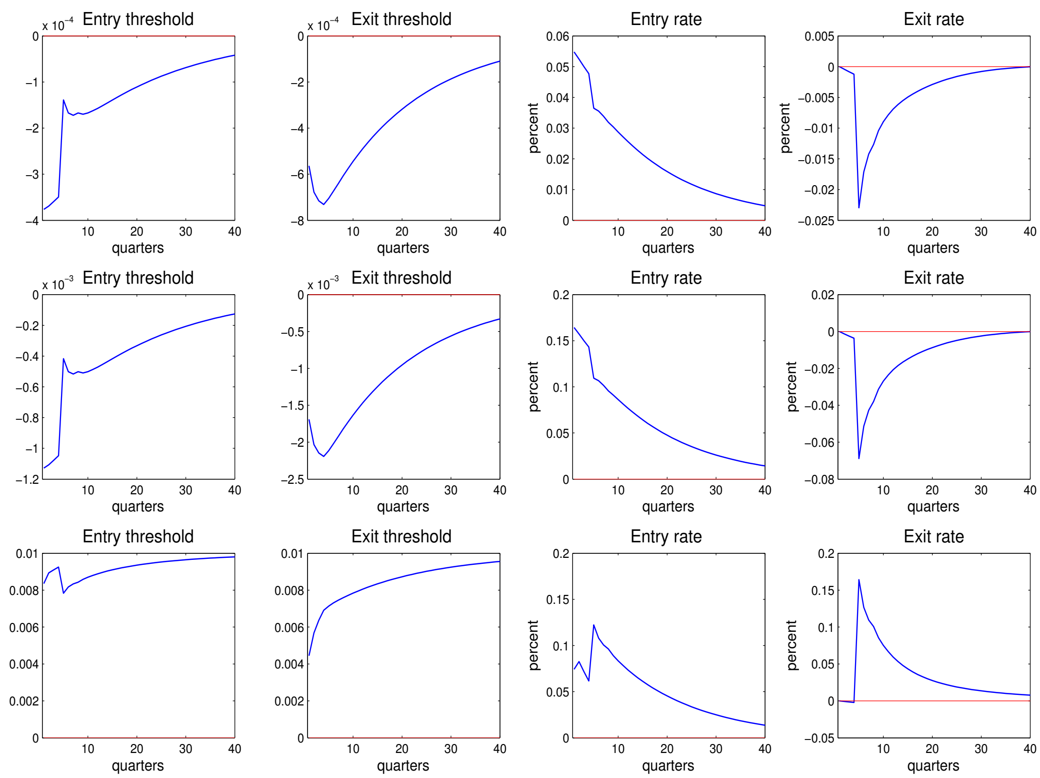

Figure 13: Four quarters of time to exit is assumed. Impulse responses of entry and exit to a one percent increase in nonrival investment-neutral technology z_t (top panel), nonrival investment-specific technology x_t (middle panel), and rival technology u_t (bottom panel). All deviations are in levels.

Appendix C Job flow in the manufacturing sector for 1972:I-1993:IV

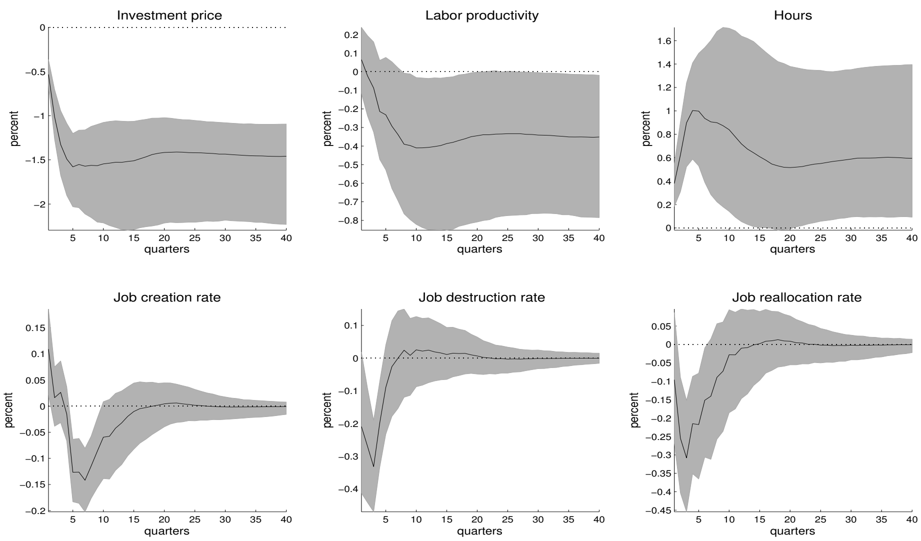

Figure 14: Impulse responses to an investment-specific technology shock based on job flow data in the manufacturing sector for 1972:I-1993:IV.

Figure 14 shows that on impact, job destruction rate falls while job creation rate slightly rises. As a result, job reallocation rate falls, which confirms the finding of Michelacci and Lopez-Salido (2007). Note that the investment shock accounts for a small fraction of job creation and destruction rates in Figure 15. Not surprisingly, the correlation between the reallocation shock and the investment-specific technology shock is low in this sample.

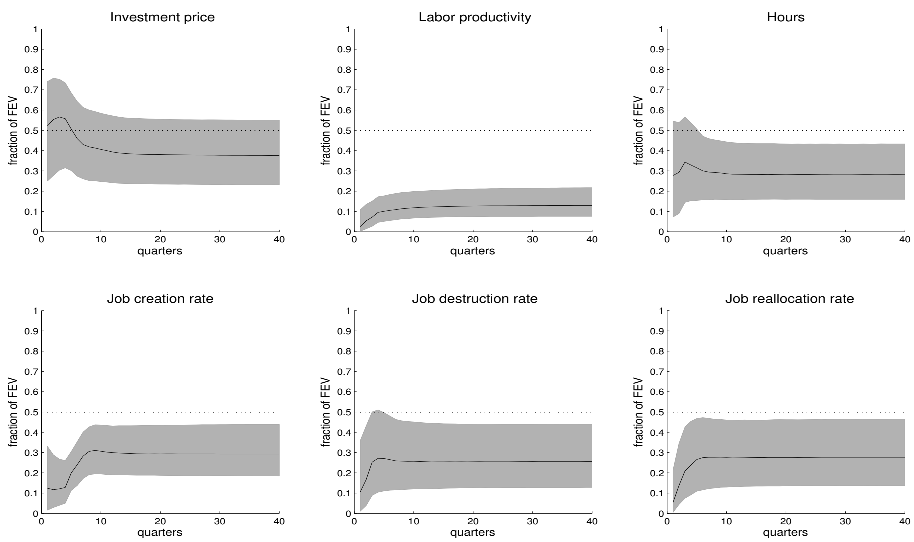

Figure 15: Fraction of forecast error variance (FEV) explained by investment-specific technology shock based on job flow data in the manufacturing sector for 1972:I-1993:IV.